APPLICATION OF INVERSE MODELING TO PERFORMANCE-BASED ARCHITECTURAL DESIGN IN THE EARLY STAGE

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APPLICATION OF INVERSE MODELING TO PERFORMANCE-BASED ARCHITECTURAL DESIGN IN THE EARLY STAGE

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To my parents
For their endless love, support, and inspiration

And to my beloved one, Amir

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LIST OF SYMBOLS AND ABBREVIATIONS

AEC	Architecture, Engineering and Construction
AHP	Analytical Hierarchical Process
ASF	Alternative Space Flexibility
ASHRAE	American Society of Heating, Refrigerating, and Air-Conditioning Engineers
BPS	Building Performance Simulation tools
CBECS	Commercial Building Energy Consumption Survey
CBR	Case-Based Reasoning
DoE	Design of Experiment
DOE	Department of Energy
EIA	Energy Information Administration
EPC	Energy Performance Calculator
EUI	Energy Use Intensity
GA	Genetic Algorithm
HVAC	Heating, Ventilation, and Air Conditioning
IEA	International Energy Agency
IT	Information Technology
JPDM	Joint probability Decision-Making Technique
LHS	Latin Hypercube Sampling
LIM	Linear Inverse Modeling
MC	Monte Carlo
MCS	Monte Carlo Sampling
PDF	Probability Density Functions
PoS	Probability of Success

PRD	Probability of a Relative Difference
QFD	Quality function Development
OLS	Ordinary Least Square
RMSE	Root Mean Square Error
SHGC	Solar Heat gain Coefficient
TFNs	Triangular Fuzzy Numbers
UA	Uncertainty Analysis
UQ	Uncertainty Quantification

SUMMARY

The architecture, engineering, and construction community is taking action to reduce energy consumption. Fulfilling energy performance requirements entails complex decision-making at the architectural design stage, when a large number of parameters are undecided and the level of uncertainty is high. The early stage of design, in particular, is characterized by its iterative nature of divergent phases in which design alternatives are generated and convergent phases in which alternatives are assessed and selected. It is during or at the end of these phases that decision-making occurs under considerable uncertainty. Therefore, the methods and tools applied during these phases should account for the iterative, complex, and uncertain characteristics of the design process. At present, the building industry lacks a consistent approach to decision making during the phrases of the early stage of design: The divergent phase, when concepts are generated, consists of no practical framework within which designers generate more promising alternatives regarding energy performance, and the convergent phase, when concepts are evaluated and selected, includes no algorithm within it that designers can use to validate their decisions and provide confidence in their decisions. These deficiencies necessitate a clear step-wise approach that supports the proper design exploration by generation and evaluation of design alternatives, highlights significant parameters regarding energy performance for a variety of design scenarios, allows for coupled decisions under uncertainty, and align with the iterative nature of design process.

This research hypothesizes that (1) a new systematic method based on linear inverse modeling (LIM) can generate plausible ranges for design parameters given a preferred thermal energy performance at the early stage of architectural design; and (2) the application of the proposed approach can lead to a higher probability of achieving energy efficient buildings (increase the chances of developing promising concepts),

which is the main objective of performance-based design; and finally (3) in comparison to the current prescriptive approach, the proposed performance-based method help designers with the design process by providing more design freedom and guidance. Such an approach also accounts for the iterative nature of an architectural design and promotes a step-by-step procedure for making a decision and updating information as each new decision is made. In contrast to the conventional "forward modeling" in building performance analysis in which the design parameters are considered input and the energy performance are output, the "inverse modeling" deals with the performance objective as input and the design parameters are inferred as the output of the analysis.

The study practices the proposed inverse modeling approach for making decisions regarding energy performance at the early design stages in four case studies, representing two different types of buildings in four climate zones. Such practices show the capability of the proposed inverse modeling to help designers in design space exploration, sequential decision-making, and trade-off study at the early stage of design. This method is proven to be a validate candidate for fulfilling desired energy performance and provide guidance and freedom in building design process. This thesis research contributes to the body of knowledge pertaining to building energy modeling and decision making at the early design stage, and its framework can be used by all groups of designers, the energy analysis experts as well as non-energy-expert architects, for a more informed decision-making regarding energy.

CHAPTER 1

INTRODUCTION

1.1. BACKGROUND OF THE PROBLEM

A large portion of a country's energy demand, contribution to global climate change, and depletion of fossil fuel stock is associated with the built environment and buildings. Regarding energy consumption, commercial and residential buildings in the United State account for 39% of primary energy use, 71% of electricity use, and 54% of natural gas use (EIA 2010). The architecture, engineering and construction (AEC) community have been seeking to take appropriate actions to reduce energy consumption while fulfilling the expectations relating to human comfort, health and other environmental protection issues (Hensen and Lamberts 2011). Fulfilling these global, local, and individual projects' requirements simultaneously is a difficult responsibility in the building design process, particularly during the earlier stages of design (Augenbroe 1992, Malkawi and Augenbroe 2003, Struck, de Wilde et al. 2009). The early stage of design is a vital phase of the development process due to its influence on all subsequent phases with regards to cost, quality and performance of the end product (Chong, Chen et al. 2009). A poor selection of a design concept can rarely be compensated at later design stages and incurs a great redesign expense (Okudan and Tauhid 2008).

Despite the importance, considering performance requirements at the building design stage is a complex decision-making task that involves interdependencies among variables that makes it difficult to elicit meaningful design guidance (Papamichael, LaPorta et al. 1997). Different design strategies have been practiced and a large number of simulation tools have been developed to assist the designer in their performance based decision making at the earlier stages (De Wilde, Augenbroe et al. 2002, De Wilde 2004, Hensen and Augenbroe 2004, Hopfe, Struck et al. 2005, Struck and Hensen 2007);

However, the actual performance of the built environment has shown that it's difficult to get to the desired energy performance in a building with the current approaches (Maile, Fischer et al. 2007), and more importantly, designers still request appropriate design decision support – methods and tools – for the early stage of design, when many design parameters have not been decided upon. They look for a proper decision making framework that leads them toward the desired performance level, gives them enough confidence in their decisions, and integrates more aspects of performance into the design process.

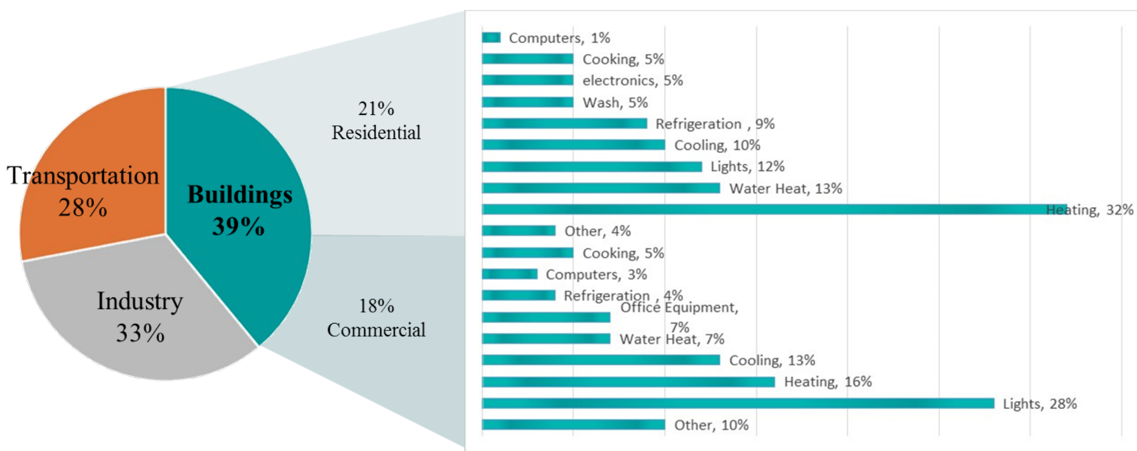


Figure 1.1 U.S. Primary Energy Consumption; Source: DOE

Performance-based design is a goal-oriented decision-making process driven by performance feedback (Malkawi 2004). In this process, it's not only sufficient to formulate the performance requirements and carry out the assessment, but more importantly is the proper management of the process that guarantees their fulfillment. In other words, both the result of the design decision-making approach as a product as well as the proper design process workflow is important for designers. Designers seek to fulfill the performance requirements, but without a proper framework for design exploration and assessment it would not be possible (Augenbroe 2011).

1.2. A REVIEW ON EARLY STAGE OF DESIGN

Design process is "an iterative search process in which designers gather, generate, represent, transform, manipulate, and communicate information and knowledge related to various domains of design concepts" (Horváth 2005). At the early stage of design, conceptual alternatives are proposed given requirements and objectives, and then will be assessed or ranked in the next phases of design (Pahl, Beitz et al. 2007). A principal aim of early design development, therefore, is the generation of promising concepts to be further developed and revised during the detailed design phase (Okudan and Tauhid 2008). In this incremental practicing and learning process, it is impossible to develop a proper solution in one shot. Instead, according to Liu et al. (Liu, Chakrabarti et al. 2003) and Wang (Wang 2002), this phase of design consists of a series of divergent and convergent steps as:

- Divergent steps consist of generating concept alternatives.
- Convergent steps relate to evaluation and selection of the best concepts among the proposed alternatives.

The goal of divergent steps is to develop promising concepts that increase the probability of producing better artifacts (Chakrabarti and Bligh 1996). This requires generating a wide range of concepts to prevent disregarding valuable ones. Often designers implicitly discard infeasible solutions based on their experience. However, many valuable alternatives might be discarded because the subjective intuitive constraints implemented by designers may be incorrect. On the other hand, the convergent process consists of concept evaluation and selection and thus identifies the alternatives that best fulfill the requirements and objectives. The assessment strategies used by designers range from none to advanced. While some designers still rely on their experience to evaluate various generated design alternatives, others tend to use performance-based strategies involving computer software simulation to assess and select the alternative that fulfills their performance objective. Selection methods range from simple decision matrices, analytical hierarchy process, methods incorporating uncertainties such as fuzzy clustering and utility theory, and also methods based on optimization concepts and heuristics.

While there are a large number of well-established methods in other design disciplines, in traditional architectural design processes an integrated and systematic method for the design alternatives generation, analysis, and selection processes in the early stages exists only rarely. This deficiency pertains to both the divergent and convergent steps of the early design process. Regarding the divergent phase, the design option generation (for energy performance) in current practice mostly relies on the designers' experience (Wang 2002), which is subject to interpretation based on the unique knowledge, expertise and insight of the designer alone.

The problem is the same for the convergent phase, which involves the assessment and selection of the most promising alternatives. In order to analyze and select the best candidate option, most AEC practitioners often use precedent- or experienced-based design to help resolve design challenges. This traditional approach tends to incorporate measurable criteria only during the advanced phases of design instead of earlier phases to validate a specific design option, rather than explore multiple alternatives. Furthermore, the simulation tools that are used in convergent phases of design for analysis are not proper for the early stage of design application; they range from reduced-order models to very detailed dynamic simulation. High-order models require extensive number of inputs including building geometry, materials properties, and details about the systems and control schedules, which is not available at the early stage of design, and designers often provide default values of selected inputs in order to take advantage of these tools. Other designers use reduced-order models that provide information with fewer inputs by applying normative equations. In both cases, designers assume default and single deterministic values for the design parameters that have not been decided yet. In other words, they are assuming that those parameters are decided and certain; at the early stage of design, however, there are high levels of unknowns or uncertainties from different sources, some of which are from the lack of information about how the design will evolve and what the values of the undecided parameters will be. These uncertainties mandate having more conscious view to the design at the earlier stages that lacks in the current approaches.

1.3. SUMMARY OF THE PROBLEM AND MOTIVATION

As mentioned before, the early stage of design is characterized by its iterative nature involving divergent and convergent phases that leads to decision-making under much uncertainty. The methods and tools applied to this stage, consequently, should account for the iterative, complex, and uncertain characteristics of design process. At present, the building industry lacks such a comprehensive approach to the early stage of design (Austin, Steele et al. 2001, Austin, Newton et al. 2002, Chong, Chen et al. 2009).

Problem Statement: The current building design process lacks an integrated and systematic method for the performance-based analysis and decision in the early stages. These deficiencies pertain to both steps of early design process:

- The divergent phase, when concepts/alternatives are generated, there is no practical and rigorous framework for designers to generate more promising alternatives regarding energy performance.
- The convergent phase, when concepts are evaluated and selected, there is no algorithm in current tools to validate the decisions and provide confidence in decision-making.

The lack of a general systematic framework appropriate for energy performance-based design, the improper energy analysis tools for early stage of design, and the absence of uncertainty consideration in the analysis and design alternatives selection make it necessary to investigate a better approach to performance-based design at early stages. These difficulties and deficiencies in current architectural design practice necessitate a clear simple step-wise approach that highlights the significant parameters regarding energy performance for the variety of design scenarios, and allow for coupled decisions under uncertainty. The ability of the method to continually change to accommodate new understanding of specifications, requirements, or preferences of other stakeholders is of importance.

The goal of the work presented here, therefore, is to support a proper generation and evaluation of design alternatives and assist the designers in their selection and decision-making by improving the design/engineering process. It incorporates the iterative nature of the architectural design as well, and proposes a systematic method of step-by-step decision-making method that updates information as new decisions are made. This study hypothesizes that a new systematic method, based on inverse modeling, can help designers estimate the undecided design parameters given preferences on performance objectives. While the current approaches use a “forward modeling” procedure to predict the performance of a design, this work applies an “inverse modeling” procedure to infer the values of design parameters considering the preferred performance. The inverse method proposed in this study probabilistically produces a large number of “likely” solutions for design parameters, incorporating constraints regarding those parameters.

1.4. RESEARCH HYPOTHESIS AND METHODOLOGY

The aim of this approach is less on finding the best solution in design decision scenario, and more on guiding designers through a design space. Here, we try to answer the questions of how conversations about performance analysis can unfold—how do they start and where do they end? What to do with thousands of similar solutions? In this study, we have proposed a new methodology, based on inverse modeling, that combines the divergent and convergent phases of design process in a way that generate a plausible range for the (undecided) design parameters that will lead to a higher probability of achieving the performance objective. In other words, we try to help designers find and choose the values of design parameters that lead them to their preferred performance with greater likelihood. In this respect, the proposed process does not aim to identify optimal solutions; it aims instead to support a more broadly intended design exploration, in which the designer can intervene to address the search process as well as extract knowledge from the generated solutions (Turrin, von Buelow et al. 2011). Based on the iterative nature of the design process, this method lets the designers iteratively make decisions about the design; and as a new decision about any parameter is made, the information will be updated which affects the estimation of the remaining undecided parameters and therefore shows how a new decision will affect other interrelated parameters.

The proposed performance-based design methodology incorporates the two different perspectives of design as a product as well as design as a process. This work, subsequently, is driven by two major hypotheses.

- Hypothesis 1: A new systematic method based on linear inverse modeling (LIM) can generate plausible ranges for design parameters given a preferred thermal energy performance at the early stage of architectural design.
- Hypothesis 2: In comparison to the current prescriptive approach, the proposed performance-based method help designers with the design process by providing more design freedom and guidance.
- Hypothesis 3: The application of the proposed approach can lead to a higher probability of achieving energy efficient buildings (increase the chances of developing promising concepts), which is the main objective of performance-based design.

These hypotheses will be tested through the creation of inverse approach models and the evaluation of the models in the following use cases:

- Enhancing the design exploration and analysis by implementing the probabilistic inverse modeling approach and validating the outputs;
- Achieving a better performance (a higher chance of achieving preferred performance) in comparison to other current strategies and tools using the proposed framework.

1.5. CONTRIBUTION OF THE WORK

This study develops an energy analysis approach that can help designers better choose design parameters based on a predefined energy performance objectives and project requirements at the early design phase. Such an approach also considers the iterative nature of architectural design and proposes a systematic step-by-step process in which decisions are made and their subsequent influence is revealed. The study, therefore, synthesizes a decision-making framework under the undecided parameter uncertainty for the architectural design at the early stage. The benefits of these hypotheses will result in:

- Informative exploration of the design option space,
- Generating the design solution space and providing more flexibility in design,
- Revealing the interactions among the parameters and performance,
- Increasing the chance of getting to the preferred target

1.6. THESIS STRUCTURE

Following this chapter, the study first defines engineering design process from the information technology (IT) point of view, and focuses on the early stage of design with the main activities and characteristics that needs to be considered. It then introduces the role of uncertainties in the design decision-making process and briefly studies the incorporation of uncertainty in analysis and design. Chapter 3 overviews the current design decision approaches in building energy performance, discusses uncertainties at the conceptual stage of building design, and emphasizes the necessity of accounting for them in design exploration and analysis. In chapter 4, the methodology of the study is explained in four main sections. Then the study provides four early design case studies and demonstrates how the proposed method can be implemented in real decision situations. Chapter 6 presents procedures for validating the hypotheses and tests if the output of this method is can lead to a higher probability of achieving energy efficient buildings. This study ends with concluding remarks in chapter 7.

CHAPTER 2

DESIGN DECISION TECHNIQUES AND THE ROLE OF UNCERTAINTIES

2.1. INTRODUCTION TO DESIGN

Engineering design is in large part a matter of decision-making. In decision theory, a decision is defined as a choice taken by an individual. Good decision-making very often is quite far from intuitive. Indeed, the good choices can be quite counterintuitive and, without a clear framework for good decision-making, it is often easy to make a poor choice. Before discussing the elements of decision-making, we distinguish between making a decision and solving a problem. When we solve a problem, we get an answer, which can be right or wrong based on the principles of physics and mathematics and the given boundary conditions. On the other hand, a decision results not in an answer, but in an outcome, which can be good or bad. The goodness of a decision depends on its consistency with the available choices, and the decision maker's beliefs on the possible outcomes of those choices, and his or her preference over her beliefs. Decision theory in design is a framework for thinking logically about choices in the presence of uncertainty on outcomes of choices. If we know the future with certainty, the main axiom of normative decision-making is: the preferred option from a set of available alternatives is the one whose outcome is most preferred, with highest utility.

Design theory is a vast field with application to a broad spectrum of disciplines (Clevenger and Haymaker 2011); in order to define design components and activities from information technology point of view, we focus on theories more closely related to the architectural design processes. Horváth (Horváth 2005) defines design process as "an iterative search process in which designers gather, generate, represent, transform, manipulate, and communicate information and knowledge related to various domains of design concepts". Here, we define design components based on the definitions Clevenger and Haymaker have provided (Clevenger and Haymaker 2012), and represent their relationship graphically in figure 2.1:

- *Variable:* a design choice to be made. A variable can be discrete (e.g., number of windows) or continuous (e.g., building length).
- *Option*: individual values of (e.g., windows to wall ratio={20%, 40%, 60%}
- *Decision*: the selection of an option (e.g., windows to wall ratio=20%)
- *Alternative:* a combination of decisions about options.
- *Stakeholder:* a party with an interest in the selection of alternatives.
- *Goal*: declaration of intended properties of alternative(s) (Van Lamsweerde 2001).
- *Preference*: weight assigned to a goal by a stakeholder (Chachere and Haymaker 2011)
- *Constraint*: limit placed on variable.
- *Requirement*: limit placed on impacts.
- *Objective:* union of stakeholders, goals, preferences, and constraints.
- *Impact*: alternative's estimated performance according to a specified goal. Estimates range from relatively quick and simple to elaborate and detailed and may or may not be easily quantifiable (C. Earl 2005).
- *Alternative Space* (Ashby 1956): All feasible alternatives for a given challenge, including explored and unexplored alternatives (Tate and Nordlund 1996). The space is sufficiently vast that it can be thought of effectively unbounded relative to designer's time and reasoning ability (Sommerville and Kotonya 1998)

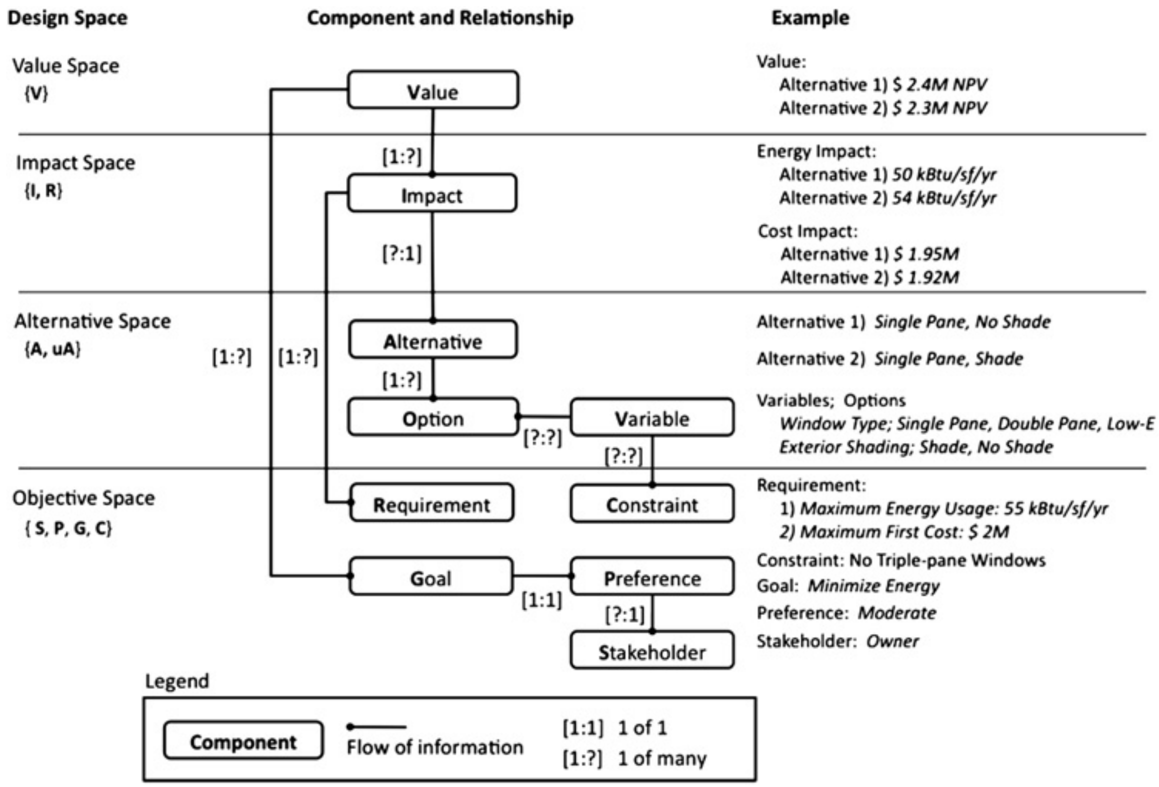


Figure 2.1 performance-based design framework, from (Clevenger and Haymaker 2011)

The earliest phases of generating and comparing alternative configuration is commonly called the predesign phase. The later stage of design, where we are well into the finalization of a particular configuration is often referred to as the detailed design phase. While much of the design literature discusses these design phases as separate and distinct, and may even offer different forms of analysis for them, there is in fact no formal distinction between the phases.

The early stage of design is a vital phase of the development process due to its influence on all subsequent phases with regards to cost, quality and performance of the end product (Chong, Chen et al. 2009). A poor selection of a design concept can rarely be compensated at later design stages and incurs a great redesign expense (Okudan and Tauhid 2008). Considering the impact choices made during conceptual stage have on the success of the design solution, it is important to have the performance assessment from the earlier stage of design decision-making (Turrin, von Buelow et al. 2011). Figure 2.2

shows the traditional versus preferred design process and the importance of informed decision-making at the early stage of design, as suggested by MacLeamy (MacLeamy 2004).

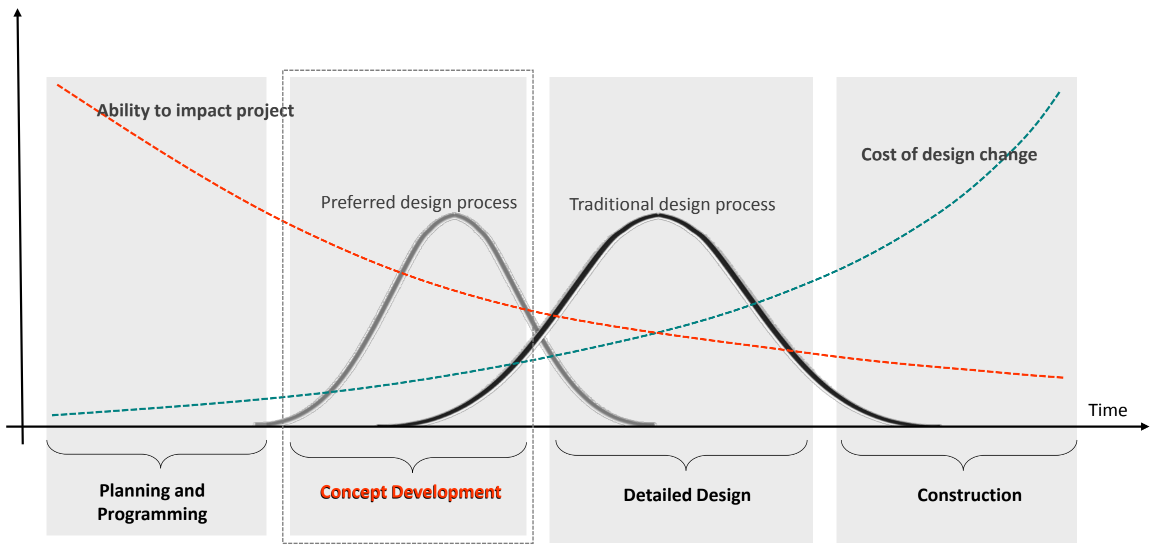


Figure 2.2 Traditional and preferred design process, from MacLeamy, 2004

2.2. CONCEPTUAL DESIGN PHASE

At the early stage of design, conceptual alternatives are proposed given requirements and objectives, and then will be assessed or ranked in the next phases of design (Pahl, Beitz et al. 2007). A principal aim of early design development, therefore, is the generation of promising concepts to be further developed and revised during the detailed design phase (Okudan and Tauhid 2008). In this incremental practicing and learning process, it is impossible to develop a proper solution in one shot. Instead, according to Liu et al. (Liu, Chakrabarti et al. 2003) and Wang (Wang 2002), this phase of design consists of a series of divergent and convergent steps as:

- *Divergent steps* consist of generating concept alternatives.
- *Convergent steps* relate to evaluation and selection of the best concepts among the proposed alternatives.

2.2.1. Divergence Phase in Conceptual Design Process

The goal of divergent steps is to develop promising concepts that increase the probability of producing better artifacts (Chakrabarti and Bligh 1996). This requires generating a wide range of concepts to prevent disregarding valuable ones. Broadbent (Broadbent and Ward 1969) emphasized the importance of generating design alternatives and argued that there are many designers who consider only the analysis/optimization and selection of solutions, rather than the creative step of developing alternative layouts of these solutions. Often designers implicitly discard infeasible solutions based on their experience. However, many valuable alternatives might be discarded because of the subjective constraints intuitively implemented by designers.

2.2.2. Convergence Phase in Conceptual Design Process

The convergent process consists of concept design evaluation and concept selection and thus identifies the alternatives that best fulfill the requirements and objectives. Figures 2.3 and 2.4 graphically represent the divergent and convergent phases in the early design process, and figure 2.5 depict them in a broader view integrating the concepts of option space and alternative space.

The importance of divergent step is apparent, because a poor selection of a design concept can rarely be compensated at later design stages and incurs a great redesign expense (Okudan and Tauhid 2008). The assessment strategies used by designers range from none to advanced. While some designers still rely on their experience to evaluate various generated design alternatives, others tend to use performance-based (goal-oriented) strategies involving computer software simulation to assess and select the alternative that fulfills their performance objective. Different options may reveal novel solutions and suggest further avenues of exploration by expanding into new parts of the design solution space.

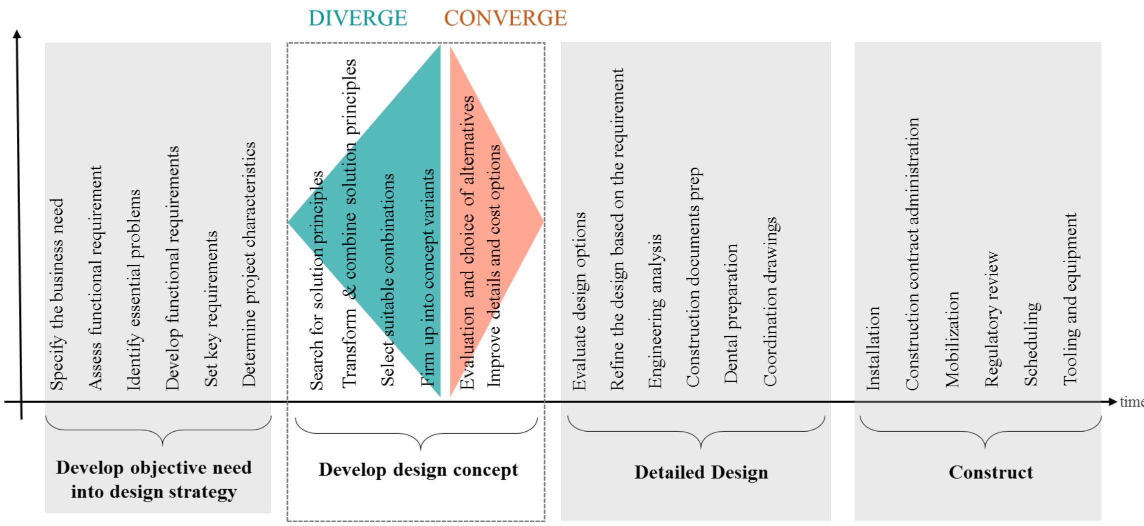


Figure 2.3 Design activities in different stages

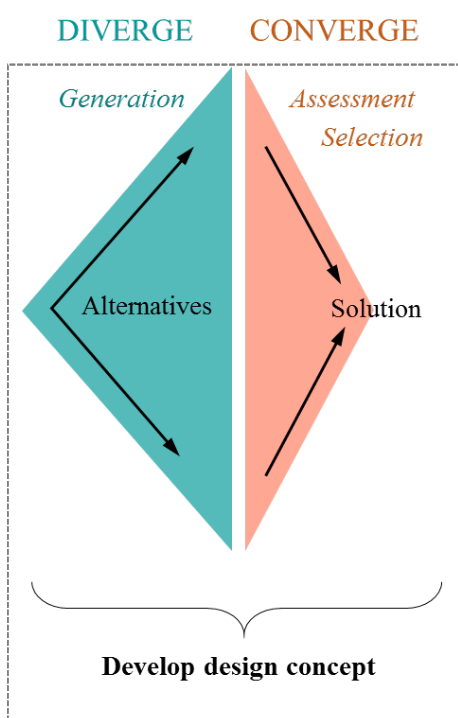


Figure 2.4 Divergent and convergent phases of design

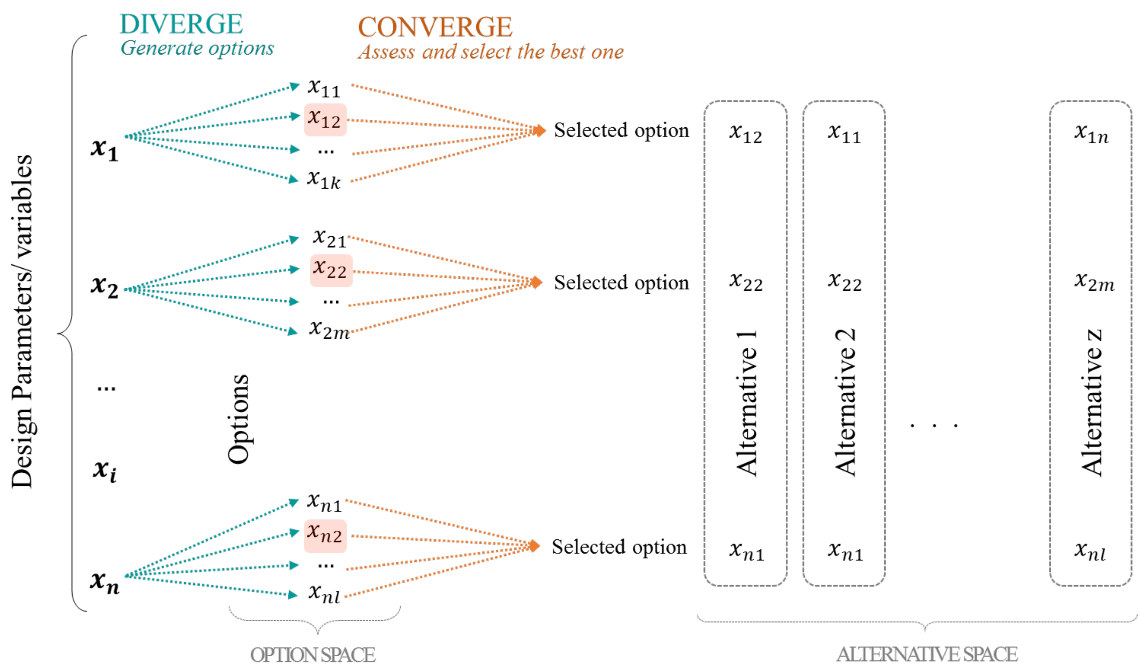


Figure 2.5 Divergence and convergence phases of design in a broader view

2.2.3. Iterative Nature of Design

The divergent and convergent phases of a design decision making are repeated for different design parameters, as well as they might be repeated along different stage of design, from vague to detailed design phase, as Liu et al. (Liu, Chakrabarti et al. 2003) proposed. There will be a pool of options for every design parameter to choose, for which a generation and selection method might be applied. At the same time, for each design parameter, concept generation and selection is carried out in an iterative and repeated divergent and convergent process with the number of solutions gradually decreased. In this sequential design process, one might backtrack at any stage and change the previously decided parameters based on the new requirement/consideration. The number of concepts is gradually decreased and only one or few solutions are left at the end of the design stage. Figure 2.6 shows two interpretations of divergent and convergent phases in design approach by Cross (Cross 2008) and Liu (Liu, Chakrabarti et al. 2003).

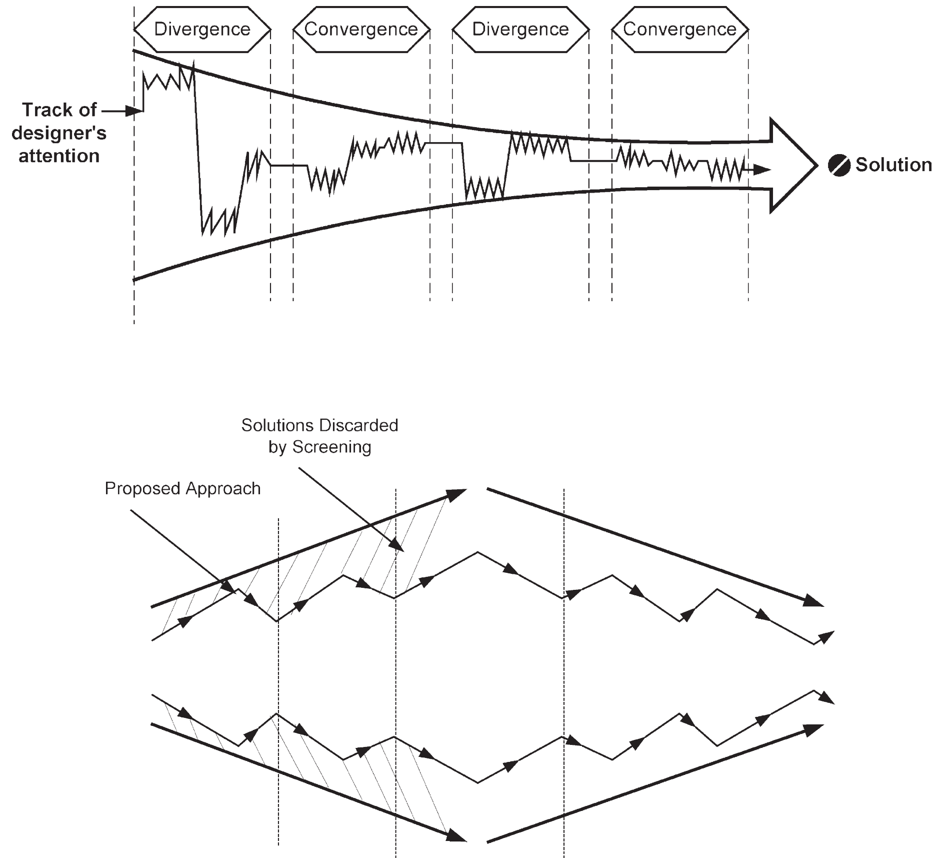


Figure 2.6 Iterative divergence and convergence phases of design; by Cross and Liu respectively

2.3. LITERATURE REVIEW ON CONCEPT GENERATION AND SELECTION METHODS

Although analysis tools vary, there are common general frameworks and methods for concept generation and the ranking and selection of the best alternatives. A brief literature review on different methods for divergent and convergent phases of design is provided in the following.

2.3.1. Divergent/Concept Generation Methods

In practice, designers often generate a few concepts based on their experiences and thereby possibly ignore a number of alternatives. Developing more promising concepts increases the possibility of creating better product or building design (Chakrabarti and Bligh 1996), as well as offers designers the freedom to choose between options. However, there rarely exists a systematic method for concept generation. Methods that generate a wide range of alternative concepts provide too many to be explored in a meaningful way. This raises another significant issue: managing the solution space is as important as generating a wide range of concepts. Therefore, developing efficient computational methods and tools for concept generation is a principal issue of improving current design decision methods and computer aided system.

Building design is very limited in concept-generation or divergent phases, and is mostly relying on designers' experience or in more systematic way, prescriptive methods such as codes. Although a few building design generation methods are developed such as *shape grammar*, they are helping designers in a non-energy related aspects and for simple algebraic rules. *Design sheet* is another example of conceptual design tool that represents algebraic equations as constraints between variables, and uses a constraints propagation approach for determining which variables are dependent on which others and find the solutions (Buckley, Fertig et al. 1992, Sudhakar 1996) (Buckley, Fertig et al. 1992). This approach solves a set of equations based on user-specified tradeoff criteria, which is suitable for well-posed problem and not the building design conceptual stage.

2.3.2. Convergent/Concept Selection Methods

Prior literature in engineering and its subfields such as manufacturing, product design and development, aeronautics and astronautics, etc., provide an array of selection methods; they range from simple decision matrices, analytical hierarchy process, methods incorporating uncertainties such as fuzzy clustering and utility theory, and also methods based on optimization concepts and heuristics. Okudan and Tauhid (Okudan and Tauhid 2008) have categorized these frameworks from the literature published between 1980 and 2008 as shown in table 1. A short description of each method is provided afterward.

Table 2.1 Concept selection methods

Concept Selection methods	Decision matrices (Ex. Pugh Charts, QFD)	
	Analytical hierarchy process (AHP)	
	Uncertainty modeling	Non-classical mathematics (ex. Fuzzy logic)
		Probabilistic mathematics (sensitivity analysis)
		Fuzzy clustering (ex. Fuzzy c-mean alg)
	Economic models (Utility theory)	
	Optimization (ex. Pareto optimality)	
	Heuristics (Ex. Genetic algorithms)	

- *Decision matrix*: which is a matrix with columns and rows indicating concepts and criteria. Any of the concepts is chosen as datum against which all other concepts are evaluated and given '+' or '-' scores, and the concepts with the highest score will be selected (Pugh 1995). Although this graphical method is simple and fast, but it does not allow for criteria to be given weight, and uncertainties are not considered. Examples of more developed decision matrices are Quality function Development (QFD) by (Coelho 2005) and the integration of QFD, morphological matrix analysis (MMA), and probabilistic optimization models (POMs) by (Fung, Chen et al. 2007).
- *Analytical Hierarchical Process*: in AHP, the problem is broken into hierarchies with the goal forming the top of the hierarchy, followed by criteria and sub-criteria, and alternatives make up the bottom. The pairwise comparison of the all criteria will determine the relative importance of each criterion (Saaty 1994) (Marsh 1993). Although AHP allows for useful comparison of criteria and alternatives, the calculations become complex as the number of criteria and alternatives increase.
- *Uncertainty Modeling*: the imprecise and incomplete design information at the early stage of design necessitates that design decision-making tools to allow for uncertainties in the concept selection process (Wang 2002). Three branches of mathematics that incorporate uncertainties are: *non-classical mathematics*, *probabilistic mathematics*, and *fuzzy logic*. In fuzzy logic, for instance, designers

describe the performance of each criterion with linguistic terms, such as "good" and "poor", which can be manipulated using fuzzy set theory (Zimmermann 1991). Tauhid and Okudan (Okudan and Tauhid 2008) introduced a method that utilizes the fuzzy information axiom by considering coupled decisions and uncertainties. Based on their method, axiomatic design helps to create a synthesized solution by "mapping": choosing a relevant design parameter in the physical domain that satisfies a given functional requirement in its domain. Figure 2.7 depicts an example of the mapping in the design process that lies in the hierarchies of domains. In order to incorporate uncertainties, Tauhid and Okudan (2007) utilize triangular fuzzy numbers (TFNs) to represent incomplete information. These techniques employ the use of complex software tools for uncertainty analysis by running Monte Carlo Sampling (MCS), and can be time consuming. Another example is the method by (Li 2004) that uses a joint probability decision-making technique (JPDM), which incorporates a probabilistic multi-criteria approach to system design. In this method, the probability of success (PoS) is used as the objective function, and is calculated by integrating the joint probability density function of the criteria over the area of criterion values that are of interest to the decision maker.

- *Economic Model or Normative Decision Theory*: economic models such as utility theory evaluate design concepts with a utility function rather than discrete ratings of fuzzy numbers. Normative utility theory utilizes a rational evaluation of design alternatives via options, expectations, and value. In Hazelrigg's description of decision making, there are three parts to a decision: the alternatives from which a choice may be taken, the decision maker's beliefs about the outcome of each choice, and a preference ordering on the outcomes. The designer's task is to find the alternative whose outcome is most preferred; i.e. the ones that has the highest expected utility (Hazelrigg 2003).. This design decision process is similar to "optimization". However the outcomes of all real decisions are in the future and can never be known with both precision and certainty. Therefore the outcome of each design alternative must be expressed probabilistically (Hazelrigg 2010). The biggest drawback of the utility theory is the inability to accommodate coupled and group decisions that exist in most design situations. Most of the methods that incorporate uncertainty, for instance, are far too complex to be implemented on a regular basis.

- *Optimization:* multi-objective optimization is a powerful means to resolve contradicting objectives in design decision-making context (Mattson and Messac 2003). Numerical techniques are used to identify optimal solutions, and in multi-objective cases, an infinite number of candidate optimal solutions are available, referred to as Pareto optimal solutions. The efficient optimization methods used in generating good representations of the Pareto frontier are: normal boundary intersection method, physical programming, and normal constraint method (Okudan and Tauhid 2008). Overall, optimization techniques are inherently complex to understand and might involve advanced mathematics, which may be out of scope of a design engineer's conventional task. Additionally, when the decision search space is extremely large, optimization methods alone cannot provide efficient solutions, designers turn to heuristics to select concepts.
- Heuristics: The big challenge of different methods of concept selection techniques and optimization relies on finding better approaches to find a handful of concepts from the many possible, and then perform detailed analysis on each of these concepts. Genetic algorithm (GA) is a stochastic optimization technique that mimics nature's evolutionary process and uses nature-inspired operators to evolve designs of improved performance. It employs Darwin's 'survival of the fittest' principle and uses nature-inspired genetic operators such as crossover and mutation to promote favorable change in the population.

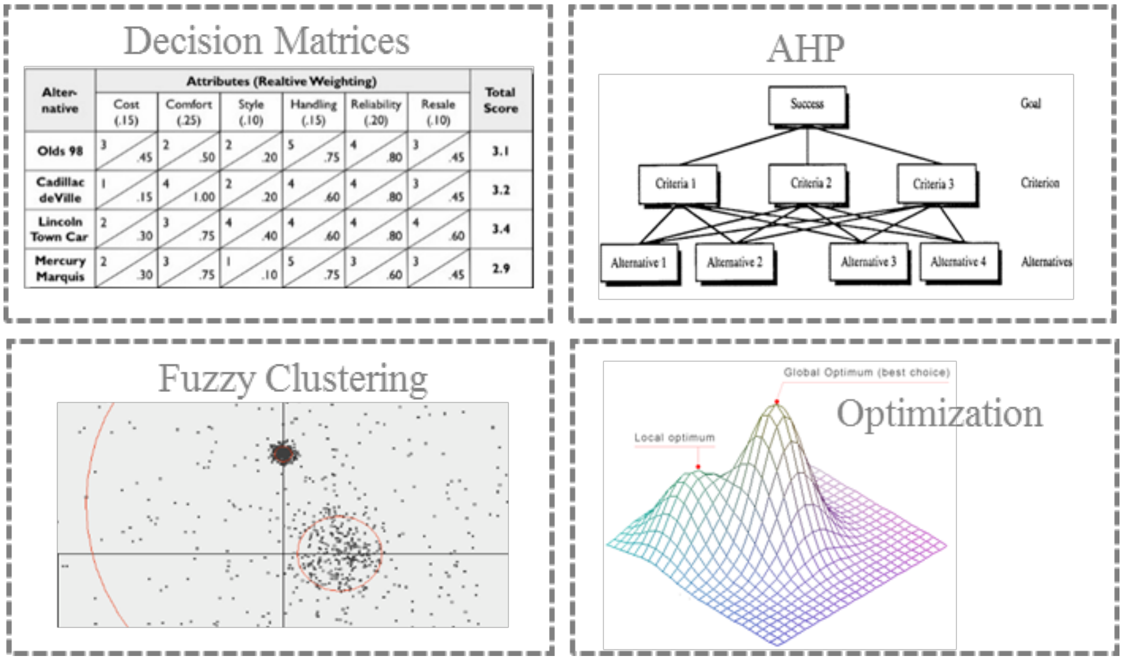


Figure 2.7 Example of different concept selection method

2.3.3. Summary

As discussed, while engineering design still lacks an effective method for concept-generation/divergent phases, there are a large number of methods developed for concept-selection or convergent phase. The convergent methods differ by the underlying principle used. Okudan and Tauhid (Okudan and Tauhid 2008) have observed that although many of these approaches have been proposed and implemented for concept analysis and selection, most have limitations including the lack of uncertainty incorporation, not having guaranteed improved solutions in spite of the computational complexity, and not considering potential coupling among various functional area. Yeh (Yeh 2002) demonstrates that different methods applied for design decision-making result in different final solutions. Thus the choice of selecting a suitable decision-making method from the pool of methods available in itself is a critical decision (Hazelrigg 2003, Okudan and Tauhid 2008).

Another important point regarding the early stage of design is that the early and later stages of design are not mathematically separate and distinct phases. The main reason why different stages have been distinguished separately is because the earlier phases are marked by considerably more uncertainty, and the analysis advocated for the early stages are more attuned to dealing with this uncertainty than the forms of analysis advocated for the later stages. At the same time we should consider that all stages of the design process are marked by uncertainty, and it is clearly necessary to account for uncertainties throughout the design process. Due to the importance of uncertainty in design decision-making and performance assessment, the next chapter is dedicated to the definition and categorization of uncertainty and its role in engineering design domain.

2.4. UNCERTAINTIES

Decision is a commitment that is made in the present to affect a more desired future. At the time of a decision, outcomes are always in the future, and the future cannot be known with certainty and precision. Therefore, we cannot say precisely and confidently what will be the outcome of a decision. We can only make a prediction that spans a range of possible outcomes and assign a probability to each possible outcome (Hazelrigg 2010). For a better clarification, the concept of uncertainty and risk are discussed in the following section by using the philosophical background literature, and the role of ignorance, and surprise.

2.4.1. Introduction to Uncertainty in Knowledge Society

We are entering the age of the knowledge society. In this world, scientific uncertainties that are caused by unexpected results are increasingly becoming part of a wider society. Originally, the term knowledge society was used to indicate the growing importance of expert knowledge as a structuring component in social relations and organization. However, as Ludwik Fleck (Fleck 1979) observed “every new finding raise at least one new problem: namely an investigation of what has just been found”. New knowledge, in turn, allows for new options without delivering secure criteria for how these new options need to be handled. “New knowledge also means more ignorance!”

Novel things, therefore, always include elements of surprise, uncertainty, and the unknown, all of which are located outside the sphere of prediction.

2.4.2. Uncertainty Definition

Uncertainty is a state when knowledge is limited and it is hard to describe the current or future state or outcome. The concept of uncertainty has been around for a long time; starting with Socrates and Plato, philosophers doubted whether scientific knowledge, no matter how elaborate, sufficiently reflected reality (Tannert, Elvers et al. 2007). They realized that the more we gain insight into the mysteries of nature, the more we become aware of the limits of our knowledge about how 'things as such' are (Gross 2010). These limitations to our understanding also make it impossible to foresee future events or the effects and implications of decisions with certainty.

To understand uncertainty better, we can draw a schematic map of various forms of uncertainty, beginning with a distinction between our knowledge and ignorance. Our schematic approach, the 'igloo of uncertainty' has been partly inspired by Faber and Proops (Faber and Proops 2013). As you see in this graph 2.8, the future events and their prediction can be categorized in two main parts, knowledge and ignorance. When we are talking about the knowledge, it means that we know the probabilities. When we talk about ignorance, it means that the probabilities are unknown. In this context, we can distinguish between closed and open knowledge with respect to risk—analogous to closed and open ignorance with respect to danger.

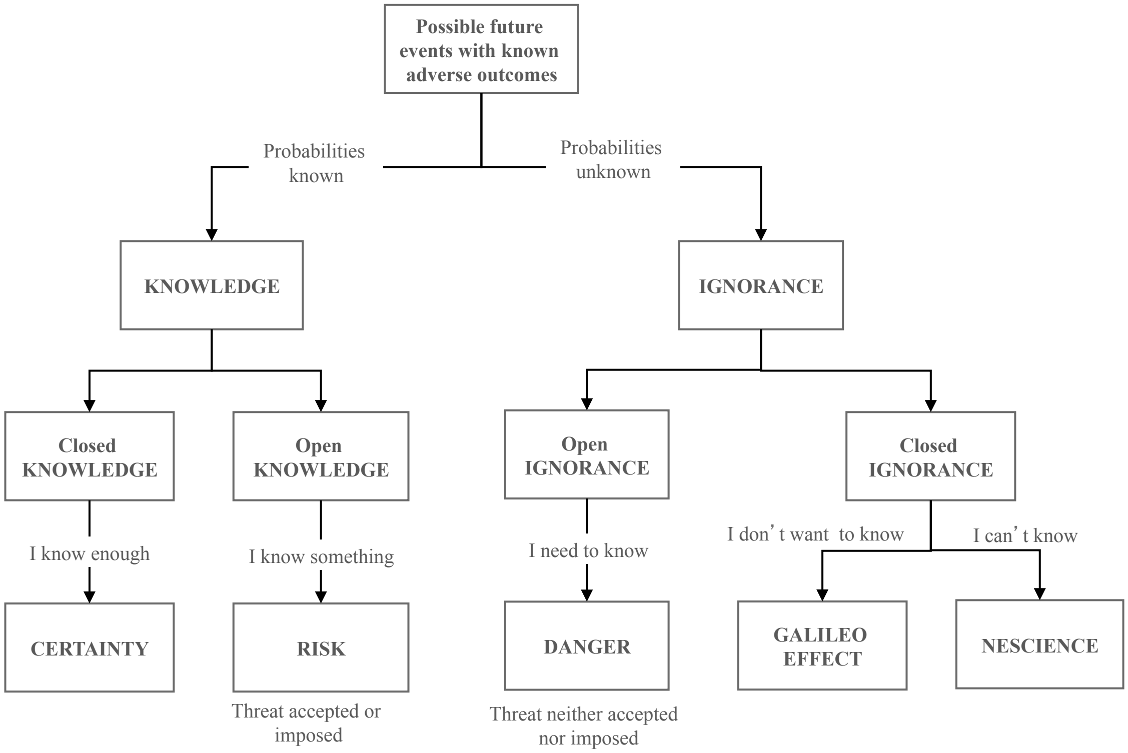


Figure 2.8 Field of uncertainty

- *Closed knowledge* means comprehensive knowledge or the certainty that an event will happen in any case.
- *Open* knowledge, by contrast, means that there is sufficient information available to perform a risk assessment, and to give rational and responsible advice. Open knowledge is caused by the gaps in our knowledge and such gaps can be successfully diminished by research,
- *Closed ignorance*; if the ignorance is due to our cognitive systems, it is called closed ignorance, an absence of knowledge (Gross 2007). Closed ignorance also results from rejecting or ignoring available knowledge, which we refer to as the 'Galileo effect'—inspired by the cardinal in Bertolt Brecht's play Galileo, who refused to look through a telescope in order not to accept the knowledge that the planets revolve around the sun. Not surprisingly, the Galileo effect is itself a risk factor and increases danger, although it can be overcome. A change in attitude

would transform closed ignorance into open ignorance, which can, at least in part, be addressed by learning or by research.

- *Open ignorance*; here the ignorance presents a greater challenge. If the cause of ignorance is a lack of knowledge, which cannot be reduced owing to stochastic and the randomness of the matter under study, it is open ignorance.
- *Risk and danger*: Risk is the probability of a harmful event multiplied with the amount of expected harm that the event will inflict. The risk from a certain event allows both the type of possible events and their probability to be known, which thereby allows the risk to be quantified. Dealing with ignorance and danger differs from risk taking or risk limiting, since Ignorance falls outside of the realm of risk. Dangers are defined in terms of the possible outcomes of a given situation. To understand the potential adverse effects of a decision, we therefore require an approximation of the quality of dangers in any given event. A prerequisite for turning danger into risk, either by accepting it or by being subjected to it, is acquiring knowledge about the danger, its nature and its probability.

2.4.3. Categories of Uncertainties:

The nature of uncertainties and how one deal with them depends on the context and application. Uncertainty in engineering can be formally classified as “aleatory uncertainty” and “epistemic uncertainty” (Swiler and Giunta 2007). Aleatory uncertainty refers to an inherent randomness in the behavior of the system under study. Alternative designations for aleatory uncertainty include variability, stochastic, irreducible, and type A uncertainty. It arises because of natural, unpredictable variation in the performance of the system. The knowledge of experts cannot be expected to reduce aleatory uncertainty although their knowledge may be useful in quantifying the uncertainty. Thus, this type of uncertainty is sometimes referred to as irreducible uncertainty.

Epistemic uncertainty arises from a lack of knowledge about the behavior of the system and the appropriate value to use for a quantity that is assumed to have a fixed value in the context of a specific application. Epistemic uncertainty can be also termed state of knowledge, subjective, reducible, and type B uncertainty (Helton and Davis 2003). Epistemic uncertainty can, in principle, be eliminated with sufficient study and, therefore, expert judgments may be useful in its reduction.

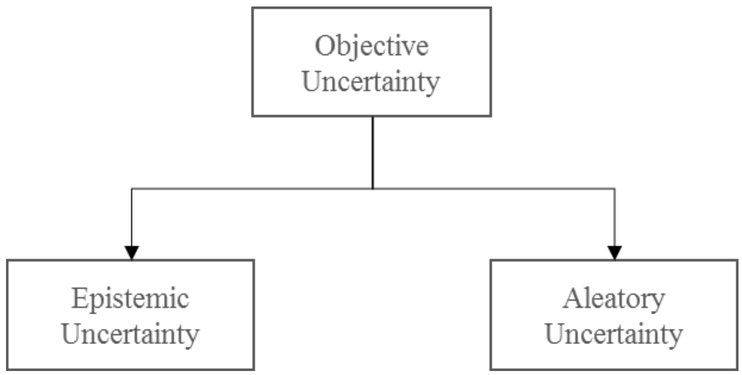


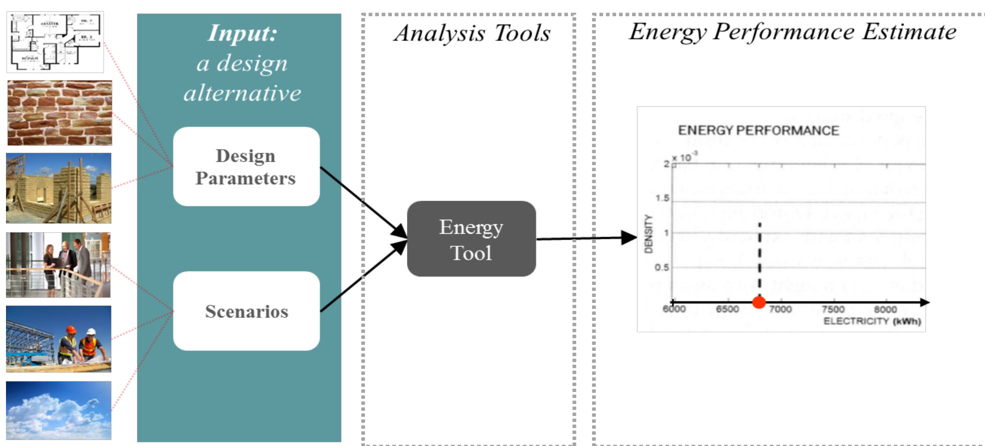
Figure 2.9 Category of uncertainty

If sufficient data is available for characterizing aleatory uncertainties, probabilistic methods are commonly used for computing response distribution statistics based on input probability distribution specifications.

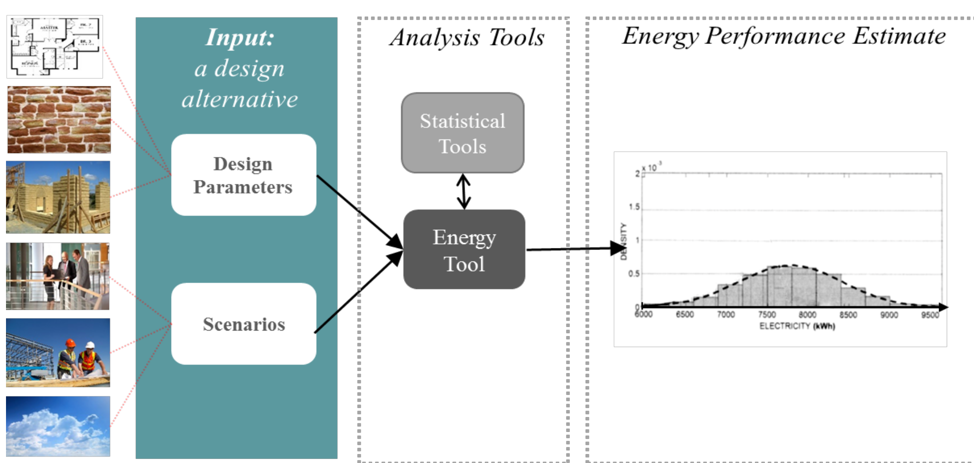
In engineering design, where models are used to analyze and predict the design, the uncertainties come from a variety of sources: physical parameter uncertainty, model inadequacy (i.e. model form uncertainty), observation errors, and unknown longitudinal (e.g., deterioration) effects. Uncertainty in model inputs reflects the variation of parameters under partly specified and partly unknown conditions. Even if model input parameter uncertainty is ruled out, i.e., all required input parameters can be assigned the prior values, the prediction will not equal the true outcome values of the process as there will always be a certain level of model inadequacy (aka model form uncertainty) and numerical uncertainty. Observation errors account for additional discrepancies between measurements and true values.

2.4.4. Incorporating Uncertainties in Engineering Design Process

Probability theory is the mathematics used for uncertainty analysis, and is a framework for thinking about the future by considering uncertain parameters probabilistically. The models commonly used for design analysis are physics-based models and are deterministic by nature, but we can use them in a non-deterministic way by replacing point values for the parameters with histograms or probability distributions. These distributions quantify the uncertainty in the variables. Figure 2.10 shows deterministic versus probabilistic approaches in building energy analysis.



(a)



(b)

Figure 2.10 Deterministic (a) versus probabilistic (b) approaches in building energy analysis. (Here design parameters are those related to the design geometry and materials; scenarios are the boundary conditions)

Model outcomes from a standard uncertainty analysis are presented in the form of probability density functions (PDF) representing the uncertainty in the performance outcome. Therefore uncertainty analysis requires two steps; uncertainty quantification (UQ), and uncertainty propagation in which the distributions reflecting uncertainties are propagated through the model using techniques such as Monte-Carlo (MC) sampling.

Regarding Monte Carlo Sampling: MC simulation is a method to analyze how much random variation of variables can affect system performance. It generates random numbers to stochastically model event occurrences. In order to sufficiently represent variation in the multidimensional parameter space without an overwhelming quantity of samples, the Latin Hypercube Sampling (LHS) technique may be used instead (McKay 1992). A Latin hypercube is the generalization of this concept to an arbitrary number of dimensions, whereby each sample is the only one in each axis-aligned hyper-plane containing it. Thus, LHS "fills" the parameter space more efficiently and converges faster compared to the classic Monte Carlo sampling. Only a large enough number of samples can fully represent the randomness of the nature.

2.5. CONCLUDING REMARKS

The early stage of design, as mentioned before, is characterized by its iterative nature involving divergent and convergent phases that leads to decision-making under uncertainty. The methods and tools applied to this stage, consequently, should account for the iterative, complex, and uncertain characteristics of design process. At the earlier stages of design it might be appropriate to use very cursory models. These could be, for example, very simple performance models that only crudely relate performance to gross design parameters. As we progress to the later stages of the design process, we usually turn to much more detailed models. As we progress from the very simple models to the more detailed models, the computational time required to evaluate a specific design increases; thus, our ability to examine design alternatives decrease proportionally

(Hazelrigg 2003). There is clearly a need to develop a fast and simple method that gives importance to designers' requirements and allow for uncertainty analysis.

In addition, the methods have to help designers for both generation and selection phases, and to consider the iterative nature of design. The next chapter studies the current methods and tools that are used in performance-based building design and evaluate if these approaches have any required characteristic of a proper method.

CHAPTER 3

A REVIEW OF CURRENT APPROACHES IN PERFORMANCE-BASED BUILDING DESIGN

Building design is an iterative decision making process in which the designers have to fulfill various stakeholders' objectives and are faced with enormous challenges such as climate change, depletion of fossil fuels, occupants' expectations, increasing flexibility of organizations and so on. Designing energy efficient buildings that also fulfill different global and local requirements and objectives is a complex challenge in the architectural decision-making process. The corresponding complexity of design analysis tools arise from their use of many underlying theories from diverse disciplines, mainly from physics, mathematics, material science, biophysics, human behavioral, environmental and computational sciences (Hensen and Lamberts 2011). In order to review the current approaches in the performance-based building design process at the early stage, we have to answer the following three related questions:

1. What method is used for the divergent and convergent phases of the performance-based analysis and design at the conceptual stage? In other words, what does the current building design workflow apply as an approach for generation and selection of design alternatives?
2. What models and tools are currently used for energy performance assessment at the early stages?
3. How are the unknowns accounted for evaluation of energy performance at the early design phase?

The next three sub-sections answer these questions.

3.1. THE CURRENT WORKFLOW IN PERFORMANCE-BASED DESIGN

While there are a large number of well-established practice and methods in other design disciplines, (Turrin, von Buelow et al. 2011) such as aerospace (Vandenbrande, Grandine et al. 2006) as mentioned in previous chapter, in the traditional architectural design processes, there rarely exists an integrated and systematic method for the design alternatives generation, analysis, and selection processes in the early stages. This deficiency pertains to both divergent and convergent steps of the early design process.

3.1.1. Concept Generation in Building Design

Regarding the divergent phase, design option generation (for energy performance) in current practice mostly relies on the designers' experience (Wang 2002), which is subject to interpretation based on the unique knowledge, expertise and insight of the individual designer. A few novel trends are developing as "Generative Design"; one of the examples is "Akaba" (Autodesk), a rules-based design cloud technology tool that allows designers to tell the computer the design goals after which it comes up with a number of solutions. The goals, however, are restricted to geometry, functional requirements, and any rules that can be translated mathematically. Physics-based rules such as energy performance are out of scope. Therefore, the application of such generative design tools is limited and designers still generate alternatives regarding energy performance based on their experience. The reasons behind this limitation in performance-based concept generation in design include:

- *Limited design alternative generation due to the restrictions of time and human cognitive ability:* The insufficiency in option generation is explained in experienced-based architectural design, as in other design disciplines, by restrictions of time, cost and technology (Josephson, Chandrasekaran et al. 1998, Liu, Chakrabarti et al. 2003) as well as by cognitive limits (Woodbury and Burrow 2006). Due to the limitations in these resources, designers usually consider only a narrow range of possible combinations of components and configurations (Josephson, Chandrasekaran et al. 1998). Furthermore, humans are endowed with specific and limited cognitive structures that constrain their behavior as searchers and conceptualizers of problem spaces (Woodbury and Burrow 2006).

- *Tendency of designers to design in a specific direction:* Darke (Darke 1979) emphasizes that, unlike other disciplines, early in the architectural design process the architect tends to identify a strongly preferred design direction, with limited design objectives and a clear concept, a so called primary generator.

The experienced-based approach for design alternative generation shows reliance on the ability to "know how to design" (Austin, Newton et al. 2002), which involves subjectivity and can be full of risks and threats to a good solution (Darke 1979). In addition, as Flagler and Haymaker (Flager and Haymaker 2007) argue, this causes design processes to focus on a relatively narrow range of possibilities, leaving a broad area of the design unexplored. This situation can be improved if they are presented with a wide range of concepts using computers, in which a wide variety of principles can be considered; and at the same time, they are not overwhelmed with all of the possibilities, but only the promising concepts.

3.1.2. Concept Selection in Building Design

The problem is the same for the convergent phase, which involves the assessment and selection of the most promising alternatives. In order to analyze and select the best candidate option, most AEC practitioners often use precedent- or experienced-based design to help resolve design challenges. This traditional approach tends to incorporate measurable criteria only during the advanced phases of design instead of earlier phases to validate a specific design option, rather than explore multiple alternatives. The reasons for the reluctance of designers to use performance-based tools at the earlier stage for energy analysis can be categorized as follows:

- *The complexity of building design and the difficulty of energy performance assessment*: There are a wide range of disciplines and many complexities in building design, and many factors to be considered in any design problem, some quantifiable and others subjective (Darke 1979). Effective design planning requires the application of techniques that can account for the complexity and non-linearity of the design process (Austin, Newton et al. 2002) and a systematic exploration of design space (Bazjanac 2008),which is not available in current practice..
- *The large number of undecided parameters*: Owing to the imprecise and incomplete design information available at the early design stage that arises from the large number of parameters that are not decided upon, it is difficult to assess and predict the performance. This lack of information, which can be categorized as a type of uncertainty that associates with how a building design may evolve complicates decision making at early stages. This issue will be discussed in detail in the next section.
- *The uncertain performance prediction due to other uncertainties*: The unavoidable uncertainty in decided-upon parameters such as material properties, scenario of use or other boundary conditions, as well as the inherent imperfection of any model as a representation of reality, lead to uncertainty in outputs and make the value of deterministic analysis questionable. The current performance evaluation methods and tools have not accounted these uncertainties and their associated risks and are generally planned based on static and “foreseeable” point estimates (Oehmen and Seering 2011).

- *The multi-criteria nature of the design*: Building design is inherently about fulfilling many performance requirements at the same time (Augenbroe 2011). In most design decision making situations, multiple criteria exist that often contradict each other; by participation of several decision makers with varying preferences, the analysis and decision making becomes more complicated.

When designers use energy analysis tools to compare limited design alternatives, the vast amount of time needed to model and assess design alternatives is a hindrance at the earlier stages of design (Flager and Haymaker 2007). A few studies have emphasized the need to develop a more robust framework for design alternative generation, evaluation, and selection, most of which have addressed non-energy related performances. Caitlin Muller and John Ochsendorf (Mueller and Ochsendorf 2013) have proposed an integrated computational approach for incorporating structural considerations into the earlier stages of architectural design process. Using interactive evolutionary algorithms, they help designers explore a broad range of structural design problems. The general procedure is to randomly initialize a first generation of candidate designs, evaluate the fitness of each generation, identify the top performers, and use them to create a subsequent generation by combining and mutating.

Some authors have addressed energy-related design procedures using optimization and heuristics. Welle et al. (Welle, Haymaker et al. 2011), for instance, have developed a methodology to optimize design in respect to thermal performance by implementing full design of experiment, (DoE). Another line of research by Caldas has proposed a generative design system, using genetic algorithm (GA) combined with lighting and thermal analysis to generate performance-driven design options, such as for patio houses (Caldas 2011), building façade elements (Caldas 2008), or other architectural elements (Caldas 2002). Turrin, Buelow and Stouffs (Turrin, von Buelow et al. 2011) have combined this same technique with parametric modeling to achieve a performance-oriented process in design, with specific focus on building geometry. However, the majority of optimization techniques used such as GA are heuristic procedures that may find solutions for well-defined problems; in the complex, ill-defined nature of the building design process, particularly at the earlier stages of design where many of the parameters have not been determined, it's questionable if their outcome remains valid after design proceed in un-predictable directions.

Optimization techniques seek an optimal solution by minimizing or maximizing an objective function. While optimization techniques can find the best solution for some of the design parameters, there are some issues that make their application in early design impractical or arguable; (1) in the building design process, we do not seek to identify purely one "optimal solution"; we aim instead at supporting more broadly feasible solutions that fulfills the performance requirements while giving the designers freedom and creativity to move toward different design directions. (2) A good approach in design is not the one that only leads to a better solution as a product, but also helps designers in the process of design through understanding the problem itself: the importance of each design parameter, relationships between parameters, and the effect of one decision on the next decisions. The current application of optimization in building design lacks the ability to help designers in all dimensions of the complex design process. (3) The building design practice in reality is an iterative process in which many backwards might happen in each divergent-convergent phase as different requirements and constraints are being evaluated and decisions are being made iteratively. The large amount of time and high cost of running full design exploration and optimization in each stage while some might be refined/altered as design proceed make their implication hard, if not impossible, for the architectural design stage.

3.1.3 What is the Workflow in Current Approaches?

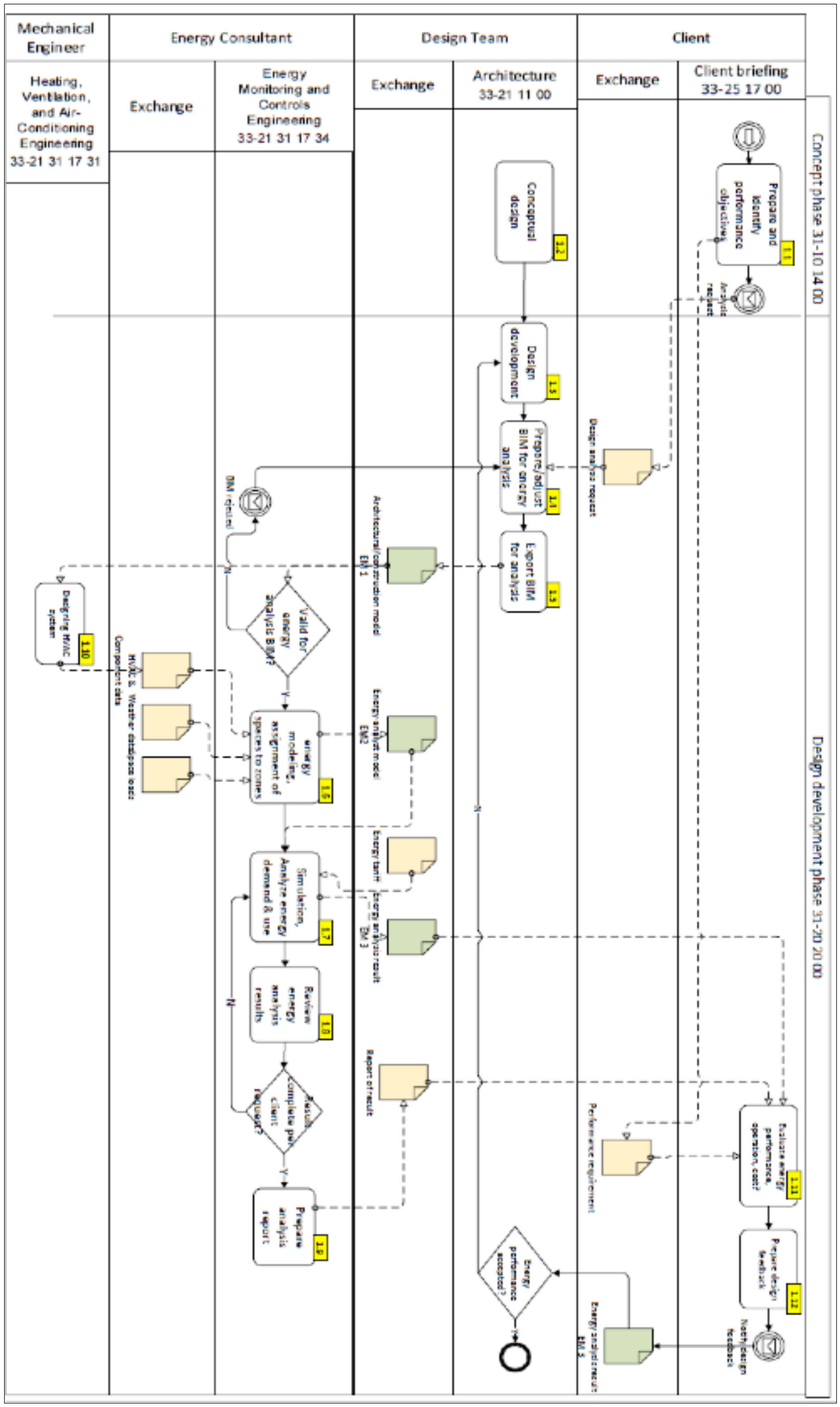
Independent from the energy performance analysis means (diagrams, mathematics, simulation tool, etc.), and based on the methods currently used for generation and selection of design alternatives, it's important to outline the general workflows implemented in current practice and the literature. To answer this question, we look at the purpose of implementing performance assessment in current approaches, which can be one of the following:

- To verify if a proposed design fulfills the performance requirements. The question being asked is "does this design satisfy my performance objective?" (Figure 3.1; source is the author's previous work)
- To rank-order design alternatives in a comparative analysis. The question being asked is "which design has higher performance as measured by a performance indicator?" (Figure 3.2; source is the author's previous work).

In the common practice at a few stages of architectural design, a narrow ranges of alternatives, derived mostly from designers' experience (subject to the time and cognitive limits) are generated for limited numbers of design parameters and then evaluated or ranked based on output from analysis tools. These evaluations or rankings are performed to answer one of the above questions, instead of asking:

- What designs satisfy my performance objective, or have greater chances of meeting objectives at final design?

The prevailing approaches, therefore, do not help designers in generating design alternatives in the divergent phase, but are mostly for performance analysis- without any particular selection method- in the convergent phase.


Mechanical Engineer
Energy Consultant
Design Team
Client
Heating, Ventilation, and Air-Conditioning Engineering 33-21 31 17 31
Exchange
Energy Monitoring and Controls Engineering 33-21 31 17 34
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Architecture 33-21 11 00
Exchange
Client briefing 33-25 17 00
Concept phase 31-10 14 00
Design development phase 31-20 20 00

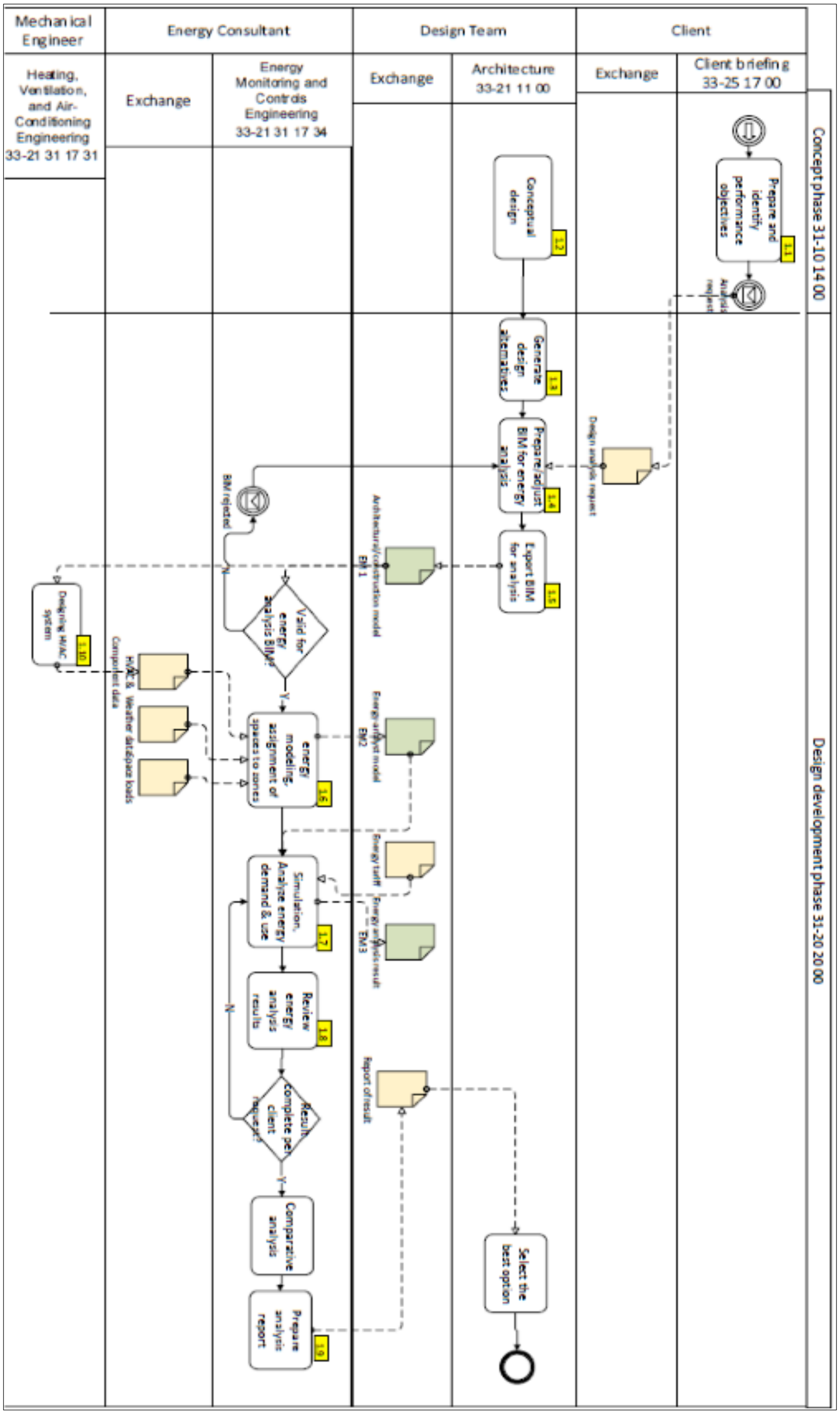


Figure 3.2 the workflow representing the energy analysis assessment for comparativ analysis

3.2. PERFORMANCE ANALYSIS TOOLS USED AT THE EARLY STAGE OF DESIGN

In the field of building energy performance analysis, *Building Performance Simulation tools (BPS)* are widely used to calculate and analyze the performance of the buildings. Building performance simulation contains the set of physic-based models and sub-models, which are employed as mathematical idealizations of reality. Many building performance analysis models and tools exist with different resolutions that allow the study of the relationships between the design parameters and the ultimate energy performance, which help in convergent phase. While some designers suggest using experience in the form of rules of thumb or case based reasoning, others advocate physics-based models and simulation during design to assess building energy performance. Table 3.1 summarizes the energy assessment tools categorization based on the resolution of the model.

Table 3.1 Categories of energy analysis tools based on the resolution

Approach	Method		Example Tools
Experience	Rules of Thumb		----
	Case-Based Reasoning		Design-MUSE
Simulation	Reduced-Order Models	Simplified Models	EPC
			CEN,
			H.e.n.k
			EDM
			MIT design advisor
		Medium Resolution	WinSim
			BuildingCalc
	High-Order Models	Whole Building Simulation	ESP-r
			eQuest
			Bsim
			EnrgyPlus

Some designers argue that trends derived from experience, articulated as design “rules of thumb,” can provide enough guidance on design. (Kolodner, Camp et al. 2003). A major issue is connecting observations in the real world with scientific principles and laws. Although this method promotes making that connection through generation and refinement of design rules of thumb, collecting large numbers of these simple rules and generalizing them is a difficult task (Grew, Boussabaine et al. 1999), particularly for a complex design as building energy performance. Case-Based Reasoning (CBR) is another experience-based method that takes advantage of experience by using computer-aided technique, and applies the lessons from old situation as the approach to a new problem. Domeshek et al. (Domeshek, Herndon et al. 1994) promote CBR as a candidate strategy in architectural design where the problems are open-ended and a decision maker lacks a strong domain theory to support ruled-based analysis. CBR provides access to descriptions and evaluations of previous designs as well as existing buildings (Domeshek, Herndon et al.). However, according to Clevenger et al. (Clevenger and Haymaker 2011) and Papamichael et al. (Papamichael, LaPorta et al. 1997), "Using precedent to meet building performance objective has proven to be less than satisfactory with regard to energy efficiency, and little reason exists to assume that it will be effective in addressing the recent proposed, aggressive energy performance goals".

Simulation (or virtual experiment) has become an essential part of today's performance analysis world (Schilders 2008). Different computer software simulation has been introduced starting from the 1970's (LBNL, 1982) and range from reduced-order models to very detailed dynamic simulation (Turrin, von Buelow et al. 2011). For performance-based strategies using simulation, the primary use of the energy models is for performance analysis and comparison of design alternatives. In order to implement any of these models at the early stage of architectural design, some designers use reduced-order models that provide information with fewer inputs by applying normative equations (Akhtar, Borggaard et al. 2010). The main goal with such reduced order models is not necessarily the accurate prediction of future as-built performance, but an accurate comparison of the normative performance of design alternatives, i.e. an ordinal ranking of options (Augenbroe 2011). Another goal is to enable rapid, if coarse, investigation of the factors that impact performance. An example of the reduced order model is the EPC, a normative energy model, which is a particular implementation of ISO 13790 (ISO 2008) and is relatively lightweight spreadsheet-based tool that requires little computational time (Lee, Zhao et al. 2011, Kim, Augenbroe et al. 2013).

On the other hand, high-order models are a more complete representation of a building that calculate heat, air, and moisture transport in concert with systems to control temperature, daylight, etc. with detailed numerical calculations. They require extensive number of inputs including building geometry, materials properties, and details about the systems and control schedules and output results usually hour by hour. In order to take advantage of these tools in conceptual design, some provide default values of selected inputs. Designers would gradually replace those default values with their designed choice as the design develops. Leive Weytjens et al. (Weytjens, Verbeeck et al. 2013), for instance, are developing a design tool to facilitate the integration of energy efficiency in early design phase for single-family houses in Flanders by reducing the inputs of the detailed analysis tools and adapting them to the available information of early design phase. After analyzing and identifying the important parameters related to design and their impact on the energy performance, default values are derived through a parametric study, subdivided according to an ambition level of project, and finally applied to the tools to be used for earlier design stages.

There are some tools with an intermediate resolution, such as Vasari, a standalone application built on the same technology as the Autodesk Revit platform (Autodesk 2013). The design at the early stage can be analyzed using the built-in energy modeling and analysis features. One of the fundamental concerns in all of these tools is the way they deal with undecided parameters and account for other uncertainties. In other words, although many 'simplified' or reduced-order tools have been developed to address the needs of early building design decisions, for example the MIT Design Advisor tool of Urban (2007), to our knowledge none incorporate high level of uncertainty associated with early stage. These physics-based models are inherently deterministic, and their typical use is likewise deterministic. This implies that the independent variables are known with certainty, which is not the case in general. This study focuses on such early decisions under design uncertainty with more definitions in the following section.

3.3. THE ROLE OF UNCERTAINTIES IN BUILDING ENERGY PERFORMANCE SIMULATION?

Many studies have demonstrated the significant role of uncertainty analysis (UA) in the context of building design and retrofit decisions. De Wit and Augenbroe (De Wit and Augenbroe 2002) obtained a probability distribution of number of hours not meeting thermal comfort to evaluate whether a mechanical cooling system is necessary. Moon and Augenbroe (Moon and Augenbroe 2007) evaluated two remediation actions on the basis of the probability distribution of mold growth risk days. Hu (Hu 2009) evaluated the power reliability of an off-grid solar house on the basis of risk measures that reflect occupants' preferences. Recently, Heo, Augenbroe, and Choudhary (Hu and Augenbroe 2012) demonstrated the importance of uncertainty information for energy retrofit decision-making, especially in the context of performance-based contracts prevailing in energy service companies. These studies have shown how quantitative information about risks changes the choice of the decision option.

Analysis of uncertainty and its influence on designers confidence – or risk tolerance – in decisions is essential in the exploration of the design space and the evolution of a design through decision-making (De Wit and Augenbroe 2002, Hopfe and Hensen 2011). An overview of the uncertainties in building performance analysis can help us determine which ones are to be accounted for in early design. In the building performance simulating process, the lack of information comes from different sources; the simulation may contain inherently uncertain quantities; furthermore, the (alternative) sub-models are invariably imperfect giving rise to additional uncertainties. According to the definition of uncertainty and its categorization to epistemic and aleatory, the uncertainties in building performance simulation can be found in any part of the process as depicted as figure 3.3.

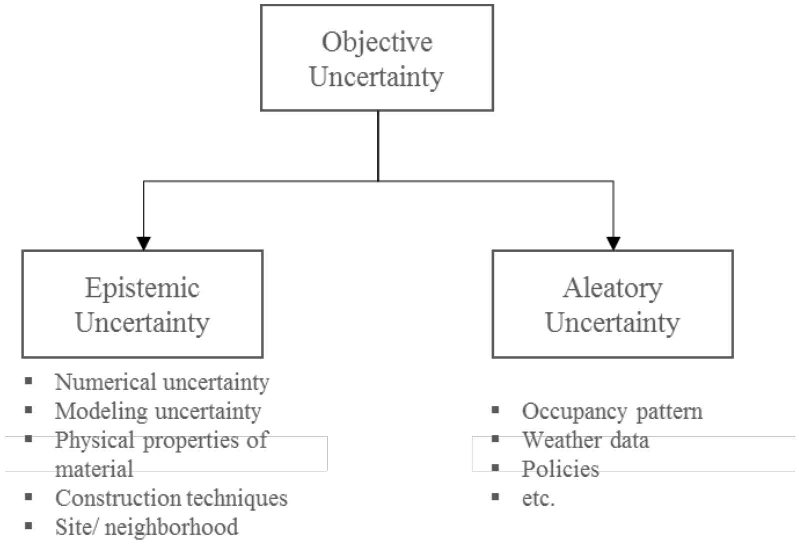


Figure 3.3 the epistemic and aleatory uncertainties in building energy analysis

As an example, for scenario variables, neither the weather nor the use of the building in the future is known with certainty, although these may be estimated within bounds. De wit has categorized uncertainty in Building Performance Tools as numerical, modeling, scenario, and specification uncertainties (De Wit and Augenbroe 2001).

Table 3.2 uncertainties in building energy analysis, as suggested by de Wit.

Type of Uncertainty		**Description**
Numerical		Arising from computation and numerical imperfection
Modeling		Associated with any model's inherent nature as an imperfect abstraction of reality.
Scenario		Associated with boundary conditions, i.e. the scenario of building use.
Design Parameter	Decided	Associated with parameters on which a design decision has been made; also called physical uncertainty and quantifies variability in material properties, etc.
	Undecided	Associated with parameters on which a decision has not been made; represents the uncertainty in the evolution of a design

- *Scenario uncertainties* are, e.g., occupancy patterns, external weather conditions, infiltration rate, and internal gains. The assessment of scenario uncertainties provides information about the design's robustness.
- *Numerical uncertainties* arise in the computational procedures and machinery used to calculate a model's dependent variables and are introduced by the numerical errors exist in the discretization and simulation of the model (De Wit, 2003). This uncertainty can be made arbitrarily small by choosing appropriate discretization and time steps, and while important, we assume such uncertainties are small compared to those in the independent variables.
- *Modeling uncertainty* is introduced by assumptions and the simplified modeling of complex physical processes inherent in any model. This uncertainty exists even if the model is developed on the basis of all relevant building properties. Every model is an imperfect representation of reality or imagined future reality and thus cannot represent reality in totality or with perfect accuracy and precision. In the case of mathematical models this imperfection comes from the choice of variables used to quantify reality and the equations that form the relations between those variables. There are many possible mathematical models that may be used to represent the physics of reality, with some being more faithful, or simply more useful, than others.
- *Design parameter uncertainty*: here we have different definition and categorization for this type of uncertainty that de Wit has called "specification uncertainty". For the parameters it is often helpful to distinguish between two types of uncertainty, which together constitute design parameter uncertainty. The first type, sometimes called physical uncertainty, encodes a lack of knowledge about the values of the parameters which have been decided upon, that is, those parameters that reflect an aspect of the building whose design is complete. A wall's geometry and construction may have been specified and materials selected,

however the properties associated with those materials, e.g. thermal conductivity, is not known with certainty because the actual values can differ from reported values due to manufacturing defects, improper installation, etc. The certainty that the choice was made does not mean certainty in the value of the model parameters associated with that choice. We call this *decided parameter uncertainty*. The second type of design parameter uncertainty is *undecided parameter uncertainty*, which encodes a lack of knowledge about values of parameters, which have not been specified. This type is relevant only during design. If the model and its results are being used to inform design decisions, not all of the design parameters have been decided upon. Indeed the model may be being used to help decide on some of those very parameters, while a decision on other parameters may be deferred until later. At the start of design none – or few – of the parameters have been decided upon and both decided and undecided parameter uncertainty is present; at the end of design, all the parameters have been decided upon and only decided parameter uncertainty is present. If we wish to make decisions at some time in the design process in the presence of undecided parameters, we need to account for the fact that we do not know what decisions we will make in the future. In other words, how the design will develop is itself an unknown. The impact on the expected performance outcome of a design decision made at an early time may be influenced by subsequent design decisions made at later times. Whereas decided parameter uncertainty is represented by a probability distribution near a chosen nominal value, undecided parameter uncertainty is represented by a distribution over all the possible choices of nominal value.

Because the final form of the design and how it will evolve are unknown at the earlier stages, undecided parameter uncertainty is of particular interest for early design decisions. Making a risk-conscious design decision (on a design parameter) when many other parameters are unknown requires accounting for the fact that we don't know what those other parameters will be after future decisions. This type of uncertainty will be high early on and thus poses a large challenge to making performance based design choices (Rezaee, Brown et al. 2014, Rezaee, Brown et al. 2014). Considering this type of uncertainty at the early design stage can also help us investigate the possibility that a later decision can counteract the impact of earlier decisions, helping to prevent situations in which what was a most preferred outcome becomes a less preferred outcome. Previous attempts have rarely dealt with on supporting performance-based decisions under undecided parameter uncertainty. Some studies have hinted at this issue, e.g. (Sanguinetti, Eastman et al. 2009, Struck, Hensen et al. 2009), the following section is an example of making this type of uncertainty an explicit focus.

3.4. EXAMPLE OF DESIGN UNCERTAINTY CONSIDERATION IN A COMPARATIVE ANALYSIS

This part of study tries to estimate the energy performance of two design alternatives in a specific design decision scenario by considering design parameter uncertainty, and to select the alternative in which we are sufficiently confident that will result in the most preferred outcome. Here we consider a decision situation to consist of a design decision to be made together with the available alternatives and some specific settings. Decisions are made on design parameters, $\mathrm{P} = \{\mathrm{p}_1, \mathrm{p}_2, \mathrm{p}_3, \dots, \mathrm{p}_\mathrm{m}\}$; at any time during design, this set of design parameters can be divided into two subsets $\mathrm{P} = \{\mathrm{P}_{\mathrm{dec}}, \mathrm{P}_{\mathrm{undec}}\}$ where $\mathrm{P}_{\mathrm{dec}}$ shows the parameters that have been decided upon, and $\mathrm{P}_{\mathrm{undec}}$ are parameters that have not been decided upon. We identify a subset of undecided parameters as to-decide parameters, $\mathrm{P}_{\mathrm{todec}} \subset \mathrm{P}_{\mathrm{undec}}$, whose elements $\{\mathrm{p}_{\mathrm{todec},1}, \mathrm{p}_{\mathrm{todec},2}, \dots, \mathrm{p}_{\mathrm{todec},\mathrm{n}}\}$ are to be decided upon in a specific decision time; For any parameter the designer would like to make decision, $\mathrm{P}_{\mathrm{todec}}$, there is a set of alternatives

$\{a_1, a_2, \ldots, a_k\}$ and a set of outcomes whose elements correspond to the design alternatives, $\{o_1, o_2, \ldots, o_k\}$, determined using an energy models. Based on the scope of this study, the outcomes are the yearly cooling and heating demands, $o_i = Q_{yC}^{a_i}$ and $Q_{yH}^{a_i}$ respectively, and stakeholders will prefer these to be low in all cases. Additionally for simplicity, we only consider two alternatives, and for notational compactness we designate these alternatives A and B.

While in current deterministic approach, one tries to investigate if "alternative A is better than alternative B", in probabilistic approach incorporating uncertainty, we should ask "are we confident that design option A will be better than option B once the design specification is complete?" Therefore instead of assigning a point value to each parameter, we apply histogram or probability distribution representing uncertainty, and consequently each outcome o_i will be described with a histogram or probability distribution.

3.4.1. Calculating Confidence in early design decisions

The metric we proposed to quantify the confidence, with outcomes o_i estimated using a given energy model, M_j, is the probability that relative differences Δ_r between two outcomes meets or exceeds a subjective threshold (Rezaee, Brown et al. 2014). We denote this PRD for probability of a relative difference, defined in the following equation for yearly cooling loads.

$$PRD_{yC,M_j} = \Pr\left[\Delta_{r,yC}\left(A, B, M_j\right) \geq \Phi\right] = \Pr\left[\frac{Q_{yC,M_j}^{A} - Q_{yC,M_j}^{B}}{\overline{Q_{yC,M_j}}} \geq \Phi\right] \quad \text{Eq. (3.1)}$$

and similar for heating loads Q_{yH}.

Here $\overline{Q_{yC,M_j}^{a_i}}$ is a normalizing yearly cooling load and $\Pr[\ldots]$ denotes the probability of what is in the brackets, determined from histograms computed from the propagation of uncertainties in P_{undec} through model M_j. The variable Φ is a decision-maker preference on the relative difference between alternatives A and B. Because there is a chance that the relative difference between outcomes may not meet or exceed that threshold, a decision-maker would need to express a preference on the chance that one alternative is indeed Φ better than another, as determined by a given model. We denoting this preferences on this chance as Ψ so that in effect, if one wishes to be confident, at level Ψ, that the outcomes estimated by model $\mathrm{M_j}$ will be Φ different at the end of the design process, then one can choose between these outcomes if:

$$\mathrm{PRD}_{\mathrm{yC,M_j}} \geq \Psi \qquad \text{Eq. (3.2)}$$

Therefore, in order to calculate the confidence in comparing two design alternative regarding energy performance, one has to define the statistical distribution of $\mathrm{Q_{yC}}$ and $\mathrm{Q_{yH}}$ which are calculated by propagating uncertainties in undecided design parameters through model.

3.4.2. Case Study

A simple decision situation related to a three-story office building in Chicago is used as a case study, for which the decision scenario involves choosing the ratio of fenestration area to opaque wall area. Two design options being considered are:

- *Option A*: the ratio of fenestration area to the whole façade area is 30 percent.
- *Option B*: the ratio of fenestration area to the whole façade area is 80 percent.

For this case study with two alternatives, the set $\mathrm{P_{dec}}$ contains some elements defining basic geometry, number of floors, orientation, etc., and $\mathrm{P_{dec}}$ contains most of the design parameters in P. $\mathrm{P_{todec}} = \{\mathrm{P_{14}}\}$, windows to wall ratio. (Table 3.3)

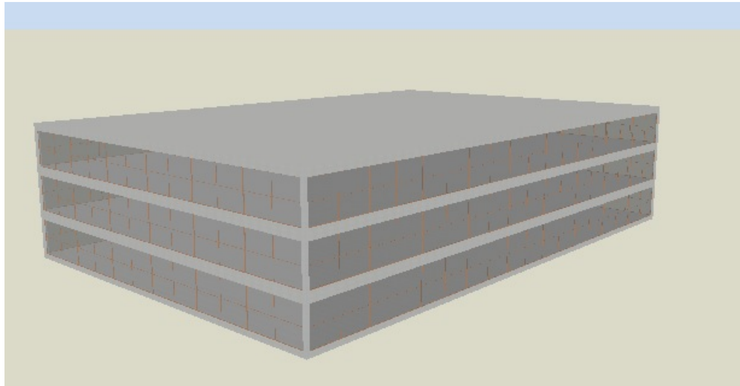


Figure 3.4 Case study of Chicago office building

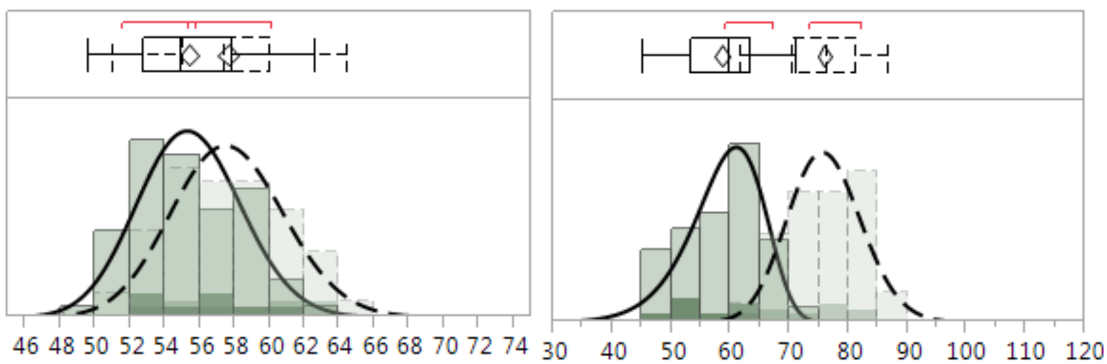
Table 3.3 The set P-undecided

Parameter	Description	Parameter	Description
$\mathbf{P_{11}}$	Roof U-value	P_{17}	Window transmittance
$\mathbf{P_{12}}$	Roof absorption coefficient	P_{18}	Wall area
$\mathbf{P_{13}}$	Roof Emissivity	P_{19}	Wall U-value
$\mathbf{P_{14}}$	Window to wall ratio	P_{20}	Wall transmittance
$\mathbf{P_{15}}$	Window area	P_{21}	Shading device factor
$\mathbf{P_{16}}$	Window U-value	P_{22}	Shading correction factor

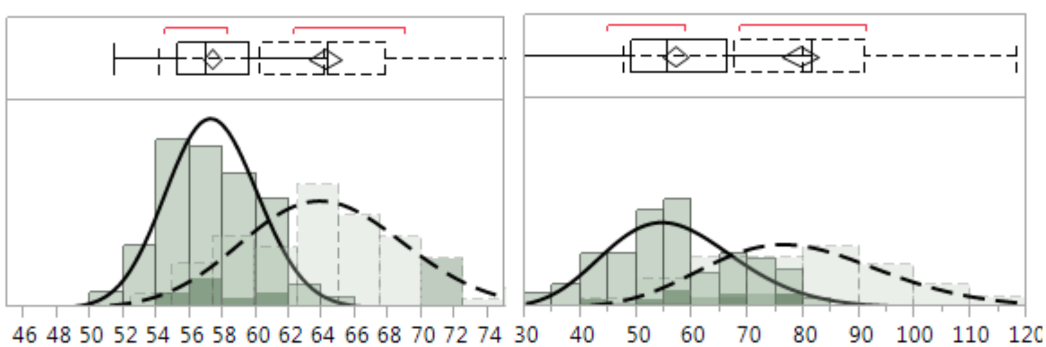
Two models with different resolutions are used in this study: EnergyPlus (Crawley, Lawrie et al. 2001) as dynamic building energy simulation program, and normative energy model, EPC, as a simple quasi-static building energy model. The results of propagating the uncertainties for the Chicago office building through both simulating model are depicted in figure 3.5. We assume that given histograms of performance indicators for two options A and B, a decision-maker has complete confidence in a decision if the two histograms do not overlap, i.e. one alternative's outcomes dominates the other's. Overlapping histograms indicate a risk that alternatives might switch places in a preference ordering: while one alternative A may be preferred to

B, as indicated by mean values of the histograms, there is a finite probability that in a particular realization of the alternatives, B could be preferred to A.

As seen in histograms, both the normative model and EnergyPlus suggest option A is preferred to option B, considering deterministically. However, the overlaps of two design options differ in two models.



(a) Cooling load, NM (b) Heating load, NM



(a) Cooling load, E+ (b) Heating load, E+

Figure 3.5 Cooling and heating loads for Chicago building, from the normative model and E+ for two options A (solid line) and B (dashed line); x-axis units are kWh/m2

Plots of PRD vs. Φ, presented in figure 3.6, shows that the probability of relative difference of 0.1 between alternatives for heating loads in both models is more than 0.75; which means that the chance that option A is better than B is more than 75%. Consequently, both models support making this decision. This confidence is reflected in the overlaps in the histograms in figure 3.5. As a result, we would have enough confidence to choose that alternative.

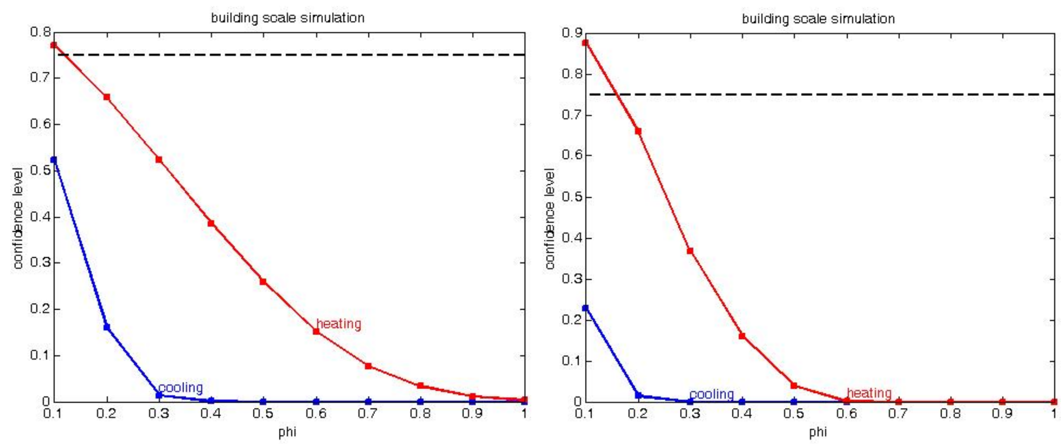


Figure 3.6 PRD vs. Φ; left NM and right E+

As depicted in PRD plots the probability of relative difference between alternatives decreases with increasing preference on that difference. As expected, for histograms with more overlapping, the chance of difference for options equaling or exceeding the preference on that difference is less. It should be noted that for histograms with no overlapping, plots would show PRD=1 for all values of Φ.

To sum up, in order to make a decision among different options under uncertainty, a decision maker needs to be confident in the outcome of that decision. One may be fully confident in a decision if the probability distribution on the performance outcome of one option favorably dominates the other probability distributions with respect to time in the design process. In the absence of a dominating effect, the notion of confidence in a decision must account for the decision-maker's attitude toward risk; that is, there is a probabilistic degree of confidence in a decision, which is fully subjective to the decision maker.

3.4. CONCLUSION

As discussed, the analysis of uncertainty and assessment of confidence in building design decisions are not included in current performance assessment techniques and tools. In this chapter we introduced uncertainty in design and an initial attempt to consider confidence in comparative design decision through introducing undecided parameter uncertainty followed by quantification of such uncertainty. In addition to not incorporating uncertainty, the lack of a general systematic framework appropriate for energy performance-based design and the improper energy analysis tools for early stage of design make it necessary to investigate a better approach to performance-based design at early stages. Therefore in the next chapter we have proposed a new methodology, based on inverse modeling that combines the divergent and convergent phases of the design process in a way that generates a plausible range for the (undecided) design parameters and will lead to a higher probability of preferred performance. In other words, we try to help designers find and choose the values of design parameters that more probably lead them to their preferred performance. Based on the iterative nature of the design process, this method lets the designers to iteratively make decision about the design; and as a new decision about any parameter is made, the information will be updated which will affect the estimation of the remaining undecided parameters and represent how a new decision will affect other interrelated parameters.

CHAPTER 4

RESEARCH METHODOLOGY

4.1. AN OVERVIEW OF THE PROPOSED APPROACH

The common procedure for performance assessment in design process is that the design parameters are fed into the physic-based model as inputs, and the (energy) performance prediction is computed as the output. Using the physical theory for predicting the performance of a set of design parameter corresponds to solving the "forward" modeling procedure. The reciprocal situation, using performance to infer the values of the parameters corresponds to the "inverse" modeling problem (Tarantola 2006). The current forward-mode of the performance assessment is compatible with the convergent phase of design process, where the design alternatives are analyzed, the performance is predicted, and the preferred alternative is selected based on the requirement.

In the performance-based design approach, the performance preference is given, and designers evaluate the decision to see if it satisfies the requirement, instead of seeking "what designs satisfy the objective performance"? In other words, the evaluation of the design -convergent phase- is performed in a forward mode. But what if we use the inverse approach to infer the design parameters that lead to the desired performance? What if the design parameters are not generated based on the subjective and intuitive nature of designers' experience or a random generation, but on the predefined and required outcome?

Mathematically, the forward problem is a many-to-one problem that has a unique solution because of the causality principle; however, it mandates that all the inputs, including design parameters, to be known. Although it's proper for analyzing the existing buildings and complete designs, it's arguable if we can apply such an approach for the early design stage, when many parameters have not been decided upon. While forward modeling is many-to-one problem that has one solution based on a set of design parameter values, the inverse approach is a one-to-many problem that may have many solutions, when different designs of the building predict similar performance, or no solution at all (Tarantola 2006). Since the main characteristic of design versus a well-posed engineering forward problem is that design leads to solutions that generally are not unique, the proposed inverse approach can be an appropriate candidate to lead to many design solutions by indicating the zones of design space where the parameters are likely to follow the desired performance. The next section introduces a new workflow based on the *inverse modeling procedure*, which can develop probabilistic estimation of parameters that can reveal suitable design.

This research uses the linear inverse approach to estimate the undecided design parameters given preferred performance objective. In order to better understand the building energy performance model and the use of inverse modeling in performance analysis, we assume "$\boldsymbol{y}$" to be the performance indicator, here building thermal load, which can be written as:

$$\boldsymbol{y} = f(x_1, x_2, x_3, \dots x_n) = f(\boldsymbol{x}) \qquad \text{Eq. (4.1)}$$

where $\boldsymbol{y}$ is a function of different variables x_i, which generally can be called $\boldsymbol{x}$.[1] $\boldsymbol{x}$ is a vector of design parameters such as orientation and wall U-value. Using the function f, the forward problem finds $\mathbf{y}$ given $\boldsymbol{x}$, while the inverse problem finds $\boldsymbol{x}$ given $\mathbf{y}$.

$$\boldsymbol{x}: (x_1, x_2, x_3, \dots x_n)\ design\ parameters \rightarrow \boldsymbol{y}: performance \qquad \text{Eq. (4.2)}$$

(forward problem)

$$\boldsymbol{y}: performance\ \rightarrow \boldsymbol{x}: (x_1, x_2, x_3, \dots x_n)\ design\ parameters \qquad \text{Eq. (4.3)}$$

(inverse problem)

[1] Note that in this manuscript, vectors and matrices are written in bold; scalars in normal font. Vectors are indicated with a small letter and matrices in capital letter

So far, x_i and y are assumed to be deterministic, calculated with single values that show we know them with certainty. In real buildings, the design parameters have not been decided upon at some design stages, and boundary conditions are not known with certainty, which leads to uncertainty in y. As described briefly in previous chapter, these uncertainties demands a probabilistic approach, which looks for the probabilities of x_i and $\boldsymbol{y}$, instead of a single values in x_i and $\boldsymbol{y}$.

The older philosophy of the inverse problem solving is stated as an optimization problem: what values of the model parameters best fit the observations? Or what is the 'best solution' implied by the data? (Tarantola 2006) This deterministic inverse technique based on exact matching leads to point estimates of unknowns without rigorously considering the statistical nature of system uncertainties, without providing quantification of the uncertainty in the inverse solution (Wang and Zabaras 2004), and without taking into consideration design evolution uncertainty. Another philosophy explicitly addresses the ambiguity associated with the ill-posed character of inverse problems. Rather than calculating a single 'best solution' according to some criterion, this approach produces a large number of likely solutions that both fit the data and any circumstances of evolving other parameters and information that might be used. This approach estimates a probability distribution of solutions upon which all subsequent inferences are based.

The latter approach is the one we are using in this study to estimate design parameters based on the desired performance. We continue describing this approach with an overview of the general techniques of linear inverse modeling, assuming that we can represent building energy performance in a linear fashion (it is stated as sub-hypothesis and is proven in section 4.3). Then we show how these techniques may be applied to the inverse problem and demonstrate their use in performance-based building design.

4.2. LINEAR INVERSE MODELING (LIM)

In linear system theory, we conventionally define a linear model of $\boldsymbol{y} = f(\boldsymbol{x})$ in matrix notation as $\boldsymbol{A}.\boldsymbol{x} = \boldsymbol{b} + \boldsymbol{\epsilon},$ in which $\boldsymbol{x}$ is a vector of design parameters (unknowns), and ϵ an error vector.

$$\begin{bmatrix} a_{11} & \cdots & a_{n1} \\ \vdots & \ddots & \vdots \\ a_{1m} & \cdots & a_{nm} \end{bmatrix} * \begin{matrix} x_1 \\ \\ x_n \end{matrix} = \begin{matrix} b_1 \\ \\ b_m \end{matrix} + \begin{matrix} \epsilon_1 \\ \\ \epsilon_m \end{matrix} \qquad \text{Eq. (4.4)}$$

Linear inverse modeling (LIM) consists of linear equality and linear inequality conditions, which is supplemented with approximate linear equations, or a target function. There are three sets of linear equations: equalities that have to be met as closely as possible (1), equalities that have to be met exactly (2) and inequalities (3):

$$\begin{cases} (\mathbf{1}) \ \ \boldsymbol{A}.\boldsymbol{x} = \boldsymbol{b} + \epsilon \\ (\mathbf{2}) \ \ \boldsymbol{E}.\boldsymbol{x} = \boldsymbol{f} \\ (\mathbf{3}) \ \ \boldsymbol{G}.\boldsymbol{x} \geq \boldsymbol{h} \end{cases} \qquad \text{Eq. (4.5)}$$

Because there is hardly solution for which $\epsilon = 0$, we use quadratic programing techniques where norm of the error term is minimized $\epsilon = \boldsymbol{A}.\boldsymbol{x} - \boldsymbol{b}$ (Van den Meersche, Soetaert et al. 2009), for example using the sum of square, $\sum \epsilon^2$, to solve these problems. The system defined with linear model we will describe in next section is an *undetermined* system since it contains more unknowns than independent equations. If the equations are consistent, there exist an infinite number of solutions. To solve such model, we randomly sample the solution space in a Bayesian way. This method returns the conditional probability density function for each unknown (Van den Meersche, Soetaert et al. 2009). The next four sub-sections are dedicated to the step-by-step procedure to define these models and equations.

4.2.1. The Formulation of the Linear Regression Model

The first step in inverse linear modeling in the current application is to construct a model that relates the design parameters to the performance function. This equality model, very roughly speaking, depicts the performance indicator y as a function of design parameters $\boldsymbol{x}$; it helps ensure the inverse problem is consistent with the involved physical laws. Although it's exactly the role of energy simulation tools to provide such a physics-based relationship and calculate y given design parameters $\boldsymbol{x}$, they require many input parameters for the energy analysis, particularly the dynamic simulation ones (Zhao 2012). Considering the large number of parameters while incorporating uncertainties, it requires supercomputers to model and compute the results in the inverse manner. For this reason, we develop a statistical model derived from a normative energy model as a representative of the physical relationship between the input and output, resulting the computation cost and time to be dramatically decreased.

The underlying assumption is that the normative energy model is a reliable representation of the relationship between building design, operational/scenario characteristics and building energy consumption (Lee, Zhao et al. 2011, Kim, Augenbroe et al. 2013), and is appropriate for early design decision-making (Rezaee, Brown et al. 2014, Rezaee, Brown et al. 2014).

We formulate the energy performance of a building as a function of design parameters and scenarios, which can be written as:

$$y \approx \mathrm{f}\left(x_{design}, x_{scenario}\right) \qquad \text{Eq. (4.6)}$$

We would like to regress the energy performance, y, on the design parameters, $\mathrm{x}_{\mathrm{design}}$. y is an energy performance indicator of building, here, thermal energy demand; $\mathrm{x}_{\mathrm{design}}, \mathrm{x}_{\mathrm{scenario}}$ are vectors of design parameters and scenario variables respectively. By considering the scenario as the variables associated with the operation of buildings as well as climate parameters, we will come up with a statistical reduced-order model as $\mathrm{y} \approx \mathrm{g}\left(\mathrm{x}_{\mathrm{design}}, \mathrm{x}_{\mathrm{scenario}}\right)$, where g is sufficiently similar to f, and can be identical for all buildings in a unique operation-and-climate situation.

Several well-established statistical methods have been used for assessing building energy consumption, such as simple normalization, general linear regression (also called ordinary least squares), corrected ordinary least squares, stochastic frontier analysis, and data envelopment analysis (Chung 2011). Although more advanced techniques usually provide more detailed results for critical conditions, the most commonly used statistical method for building stock energy profile estimation is ordinary least square (OLS). This is not only because of its simple procedure and intuitive results, but also because of its reliability and robustness advantages compared to other advanced techniques. Therefore, in this study simple linear regression has been chosen. Similar regression models have been hypothesized and proved by Fei Zhao, (Zhao 2012), as:

> "*Given feasible ranges of building design parameters, a set of inputs and the output (primary EUI) of the normative building energy model can be expressed as a linear regression model.*"

In this study, the similar sub-hypothesis can be formulated as:

> "*Given feasible ranges of building design parameters, a set of inputs and the output (thermal demand) of the normative building energy model can be expressed as a linear regression model.*"

In order to develop this model out of normative energy model, EPC, we first define parameter ranges, sample from them and find corresponding thermal load, apply global sensitivity analysis to identify the design parameters with the most significant impact, and develop a linear regression model out of it.

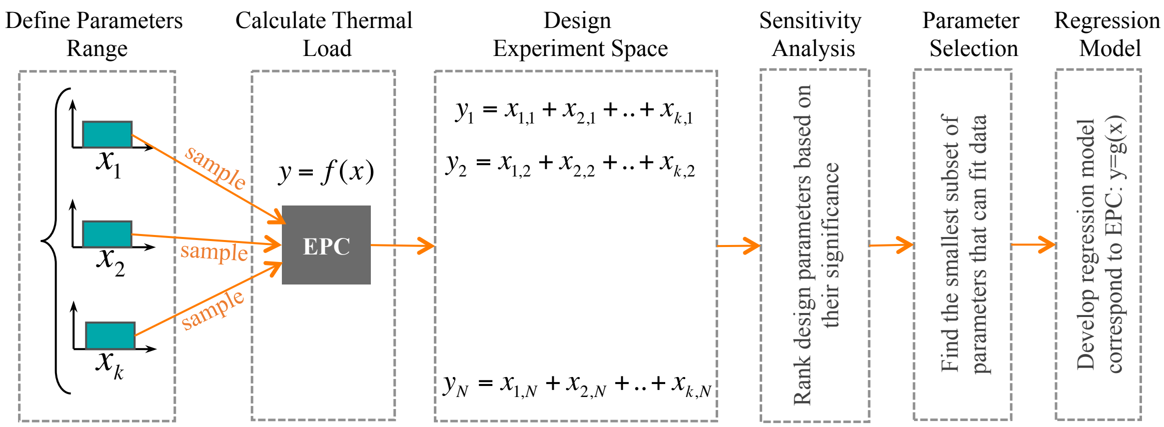


Figure 4.1 The process of developing a regression model out of normative energy model

In other words, we are going to develop a regression model, $y = g(x)$, that sufficiently fit the EPC model, $y = f(x)$. This regression model is reduced version of EPC.

4.2.1.1. Parameter Range

The first step in sensitivity analysis is to identify the ranges of parameters. For each scenario of building design, this study uses different resources to define parameter ranges, including but not limited to ASHRAE 90.1 standard and CBECS data.

Regarding ASHRAE 90.1: The American Society of Heating, Refrigerating, and Air-Conditioning Engineers sets standards that provide the minimum requirements for energy-efficient building design. These standards define the minimum energy-efficient requirements for buildings and their systems or a portion of a building in detail. They also offer the requirements for new equipment and systems in existing buildings. The criteria for checking compliance with the requirements have been determined in these standards (Handbook 2009, 90.1) (ASHRAE 2013).

Regarding *CBECS* data: The Commercial Buildings Energy Consumption Survey (CBECS) is a survey about energy consumption in U.S. commercial buildings. U.S. Energy Information Administration conducts and provides these statistical information about characteristics of the sample commercial buildings quadrennially. In this study, the information regarding the floor area, for instance, has been derived from this database. In order to protect the identities of the respondents, some building characteristics, such as number of floors, haven been concealed (EIA 2006).

Table 4.1 lists the category and selected design parameters to be used for sensitivity analysis, using normative energy model or EPC. The values and ranges for each of these parameters vary based on the buildings' operation and climate situation. Based on the four case studies we are going to test in the next chapter, here we represent the parameters ranges as well as regression models associated with these four case studies (CS) of: *CS1*: elementary school in Chicago, *CS2*: elementary school in Los Angeles, *CS3*: medium size office buildings in Atlanta and *CS4*: medium size office buildings Miami. Table 4.2 lists the parameter ranges associated with these four cases along with their references.

Table 4.1 Variable considered in the regression variable selection

Variables #		***Variable Name***	***Definition***
Form	1	Floor Area	Gross Floor Area (m2)
	2	Number Floors	Number of Floors
	3	FHeight	Floor Height (m)
	4	AR	Aspect Ratio
	5	Orientation	Orientation
Envelope	6	SWWR	S-Window to wall ratio
	7	EWWR	E-Window to wall ratio
	8	NWWR	N-Window to wall ratio
	9	WWWR	W-Window to wall ratio
	10	EHGC	Envelope heat gain capacity
	11	AL	Air Leakage
	12	Wall-UValue	Opaque UValue
	13	Wall-Abs	Opaque absorption co.
	14	Wall-Emis	Opaque emissivity
	15	Roof-UValue	Roof U-Value (W/m2K)
	16	Roof-Abs	Roof Absorption coefficient
	17	Roof-Emis	Roof Emissivity
	18	Window-UValue	Windows U-Value (W/m2K)
	19	Windows-Emis	Windows Emissivity
	20	SHGC	Windows Solar Transmittance
	21	South-SD1	South Shading Overhang (degree)
	22	South-SD2	South Shading Fins (degree)
	23	East-SD1	East Shading Overhang (degree)
	24	East-SD2	East Shading Fins (degree)
	25	North-SD1	North Shading Overhang (degree)
	26	North-SD2	North Shading Fins (degree)
	27	West-SD1	West Shading Overhang (degree)
	28	West-SD2	West Shading Fins (degree)
Internal Gain and Control	29	Cooling SP	Weekdays Cooling Setpoint (C)
	30	Cooling SB	Weekend Cooling Setpoint (C)
	31	Heating SP	Weekdays Heating Setpoint (C)
	32	Heating SB	Weekend Heating Setpoint (C)
	33	Occupancy	Occupancy (m2/person)
	34	Appliance	Appliance (W/m2)
	35	Lighting	Lighting (W/m2)
	36	DHW	DHW (W/m2)

Table 4.2 Variable considered in the regression variable selection and their ranges for four scenarios of elementary schools in Chicago and Los Angeles, and office buildings in Atlanta and Miami

Variables		***Unit***	***CS$_1$-Chicago***		***CS$_2$-LA***		***CS$_3$-Atlanta***		***CS$_4$-Miami***		***References***
			min	***max***	***min***	***max***	***min***	***max***	***min***	***max***	
1	Gross floor area	m2	100	25110	100	24180	100	27435	102	28830	Selected CBECS samples
2	Number of floors	_	1	10	1	5	1	12	1	10	Selected CBECS samples
3	Floor height	m	3.75	4.2	3.75	4.2	3.75	4.2	3.75	4.2	Kohn & Katz, 2002
4	Aspect ratio	_	0.2	5	0.2	5	0.2	5	0.2	5	Kohn & Katz, 2002
5	Orientation		0	180	0	180	0	180	0	180	_
6	S-Window to wall ratio	_	0	1	0.1	1	0.1	1	0.1	1	_
7	E-Window to wall ratio	_	0	1	0	1	0	1	0	1	_
8	N-Window to wall ratio		0	1	0.1	1	0.1	1	0.1	1	_
9	W-Window to wall ratio		0	1	0	1	0	1	0	1	_
10	Envelope heat gain capacity	J/m2K	80,000	370,000	80,000	370,000	80,000	370,000	80,000	370,000	ISO 13790, 2008
11	Air leakage	m3/h per floor area at Q4Pa	0.6	2.2	0.6	2.2	0.6	2.2	0.6	2.2	Heo, 2011
12	Opaque UValue	W/m2K	0.2	1.5	0.2	1.5	0.2	1.5	0.2	3.293	ASHRAE 90.1
13	Opaque absorption co.	_	0.43	0.83	0.43	0.83	0.43	0.83	0.43	0.83	Macdonald, 2002
14	Opaque emissivity	_	0.85	0.92	0.85	0.92	0.85	0.92	0.85	0.92	Macdonald, 2002
15	Roof UValue	W/m2K	0.1	1.5	0.2	1.5	0.2	1.5	0.2	3.293	ASHRAE 90.1
16	Roof absorption co.	_	0.43	0.83	0.43	0.83	0.43	0.83	0.43	0.83	Macdonald, 2002
17	Roof emissivity	_	0.46	0.95	0.46	0.95	0.87	0.95	0.87	0.95	Macdonald, 2002
18	Window UValue	W/m2K	0.7	3.8	1.5	3.8	1.5	3.8	1.5	7.2	ASHRAE 90.1
19	Window emissivity	_	0.46	0.95	0.46	0.95	0.87	0.95	0.87	0.95	Macdonald, 2002
20	Window SHGC	_	0.04	0.85	0.04	0.75	0.04	0.75	0.04	0.75	Loutzenhiser,2009
21	South Overhang	degree	0	60	0	60	0	60	0	60	_
22	South Fin	degree	0	60	0	60	0	60	0	60	_
23	EastOverhang	degree	0	60	0	60	0	60	0	60	_
24	East Fin	degree	0	60	0	60	0	60	0	60	_
25	North Overhang	degree	0	60	0	60	0	60	0	60	_
26	North Fin	degree	0	60	0	60	0	60	0	60	_
27	West Overhang	degree	0	60	0	60	0	60	0	60	_
28	West Fin	degree	0	60	0	60	0	60	0	60	_
29	Cooling Setpoint	Celsius	17	25	17	25	17	25	17	25	Wei, 2011
30	Cooling setback	Celsius	17	30	17	25	17	25	17	25	Tian & Choudhary, 2011
31	Heatiing setpoint	Celsius	17	25	17	25	17	25	17	25	Heo, 2011
32	Heating setback	Celsius	17	25	17	25	17	25	17	25	Heo, 2011
33	Occupancy	m2/perso n	1.6	10	1.6	10	15	40	15	40	CBECS 2003 Offices/ Knight,2003/ Illinois State Board of Education (ISBE)
34	Appliance total	W/m2	3	18	3	18	0	34	0	34	Tian & Choudhary, 2011, Dunn & Knight, 2005
35	Lighting	W/m2	5	15	5	15	0	17	0	17	Tian & Choudhary, 2011, CIBSE, 2006
36	DHW	W/m2	0	10	0	10	0	10	0	10	_

4.2.1.2. Sensitivity Analysis

Given the feasible ranges of model variables, the next step is to generate data samples and retrieve the corresponding model outcomes or response for variable sensitivity analysis using normative energy model, EPC. The response or outcome is the sum of cooling and heating load, which in this study is called thermal load, thermal demand, or energy performance. In this research, we use global sensitivity analysis to robustly estimate importance of input variables over a wide range, usually across a group of buildings. Common techniques include parametric methods such as multiple linear regression coefficients, and nonparametric methods such as multivariate adaptive regression splines (Tian and Choudhary 2012). The Monte Carlo (MC) simulation is used to generate samples for the regression analysis in ModelCenter (PHX 2013). The 2,000 samples are fed into the EPC in each case study, to compute their corresponding thermal load values using associated weather data for the type of the building under study.

The results of the sensitivity analysis are in tables 4.3 to 4.6, ordered by the most significant variables along with their estimates, standard error, t value, and p value of each term. These variables are ranked by their absolute t statistic values (negative t values indicate that the thermal energy demand would increase if these variables decrease, and vice versa). The higher the absolute value of t, the more significant is the coefficient of that variable. The highlighted ones are those that have been considered in the fitted regression model, as will be discussed in the following section. As an example, in table 4.3, the first 20 variables out of the total 38 candidate variables form the best subset, leaving out other parameters for regression model. Section 4.2.1.3 provides proof for selecting the best subset in these models.

Table 4.3 CS1_Chicago sensitivity analysis result

CS1-Chicago: Elementary School in Chicago						
Variable No.	**Variable**	**Estimate**	**Std Error**	**t Ratio**	**t Ratio**	**Prob>|t|**
4	Occupancy	154.24722	2.056716	75		<.0001*
1	Gross Floor Area	1150.8426	18.59074	61.9		<.0001*
14	Weekdays Heating Setpoint	6.0414165	0.107545	56.18		<.0001*
16	Weekdays Cooling Setpoint	-5.900398	0.109524	-53.87		<.0001*
27	Air Leakage	10.648219	0.353941	30.08		<.0001*
3	Number of Floors	2.5707562	0.09762	26.33		<.0001*
24	Windows U-Value	6.1195274	0.269069	22.74		<.0001*
15	Weekend Heating Setpoint	1.9760737	0.111199	17.77		<.0001*
18	Roof Uvalue	10.717356	0.613281	17.48		<.0001*
17	Weekend Cooling Setpoint	-1.16174	0.06825	-17.02		<.0001*
10	North WWR	11.541906	0.849691	13.58		<.0001*
21	Wall U-Value	8.1259805	0.682752	11.9		<.0001*
8	South WWR	9.6193522	0.87032	11.05		<.0001*
26	Windows SHGC	10.767873	1.079198	9.98		<.0001*
12	Aspect Ratio	1.4620514	0.179027	8.17		<.0001*
9	East WWR	6.0615204	0.871365	6.96		<.0001*
2	Floor Height	10.23426	1.944657	5.26		<.0001*
11	West WWR	3.1195306	0.871488	3.58		0.0004*
5	Appliance	0.1478993	0.058477	2.53		0.0115*
28	South Overhang	0.0250941	0.01125	2.23		0.0258*
35	West Fin	0.0164697	0.011329	1.45		0.1462
33	North Fin	-0.016077	0.011444	-1.4		0.1602
31	East Fin	-0.01372	0.011281	-1.22		0.2241
30	EastOverhang	-0.011484	0.01134	-1.01		0.3113
34	West Overhang	0.0102754	0.011448	0.9		0.3695
32	North Overhang	0.0099733	0.011464	0.87		0.3844
19	Roof Absorption	1.6619771	2.173246	0.76		0.4445
13	Orientation	0.5975547	0.876333	0.68		0.4954
22	Wall Absorption	1.5003712	2.226867	0.67		0.5005
7	DHW	-0.05426	0.08882	-0.61		0.5413
20	Roof Emissivity	1.0683876	1.764992	0.61		0.545
23	Wall Emissivity	-5.825909	12.32474	-0.47		0.6365
6	Lighting	-0.020175	0.085312	-0.24		0.8131
29	South Fin	0.0024557	0.011144	0.22		0.8256

Table 4.4 CS2_LA sensitivity analysis result

CS2-LA: Elementary School in Los Angeles						
Variable No.	**Variable**	**Estimate**	**Std Error**	**t Ratio**	**t Ratio**	**Prob>|t|**
16	Weekdays Cooling Setpoint	-13.68962	0.192242	-71.21		<.0001*
26	Windows SHGC	79.191186	1.857342	42.64		<.0001*
1	Gross Floor Area	937.00378	29.44888	31.82		<.0001*
4	Occupancy	110.84404	3.499942	31.67		<.0001*
14	Weekdays Heating Setpoint	4.8761577	0.190742	25.56		<.0001*
17	Weekend Cooling Setpoint	-2.233409	0.115695	-19.3		<.0001*
5	Appliance	1.835358	0.100666	18.23		<.0001*
3	Number of Floors	2.0408102	0.171706	11.89		<.0001*
6	Lighting	1.7672469	0.152545	11.59		<.0001*
15	Weekend Heating Setpoint	2.0199243	0.18935	10.67		<.0001*
24	Windows U-Value	-4.841894	0.458814	-10.55		<.0001*
10	North WWR	15.251148	1.513316	10.08		<.0001*
8	South WWR	14.979387	1.513207	9.9		<.0001*
11	West WWR	12.170152	1.516285	8.03		<.0001*
27	Air Leakage	-2.757516	0.614063	-4.49		<.0001*
9	East WWR	5.6841446	1.532858	3.71		0.0002*
12	Aspect Ratio	0.9784573	0.31877	3.07		0.0022*
22	Wall Absorption	7.4257142	3.845161	1.93		0.0536
2	Floor Height	5.9563475	3.422147	1.74		0.0819
34	West Overhang	-0.034315	0.019944	-1.72		0.0855
18	Roof Uvalue	1.8775007	1.093191	1.72		0.0861
35	West Fin	0.0333742	0.019525	1.71		0.0876
33	North Fin	0.0325443	0.019897	1.64		0.1021
31	East Fin	0.0324889	0.019971	1.63		0.1039
32	North Overhang	0.0247981	0.019901	1.25		0.2129
7	DHW	0.1778673	0.152697	1.16		0.2442
23	Wall Emissivity	24.962959	21.79475	1.15		0.2522
13	Orientation	1.6853455	1.497234	1.13		0.2605
19	Roof Absorption	4.0597126	3.784381	1.07		0.2835
20	Roof Emissivity	-3.098985	3.067075	-1.01		0.3124
21	Wall U-Value	-0.838891	1.169907	-0.72		0.4734
29	South Fin	-0.005597	0.019843	-0.28		0.7779
28	South Overhang	-0.004599	0.019924	-0.23		0.8175
30	EastOverhang	-0.003403	0.01965	-0.17		0.8625

Table 4.5 CS3_Atlanta sensitivity analysis result

CS3-Atlanta: Mid Office in Atlanta						
Variable No.	**Variable**	**Estimate**	**Std Error**	**t Ratio**	**t Ratio**	**Prob>|t|**
16	Weekdays Cooling Setpoint	-8.985467	0.157004	-57.23		<.0001*
1	Gross Floor Area	1247.4993	23.53217	53.01		<.0001*
14	Weekdays Heating Setpoint	5.9475281	0.159132	37.37		<.0001*
5	Appliance	1.2795027	0.037241	34.36		<.0001*
26	Windows SHGC	41.879187	1.565178	26.76		<.0001*
3	Number of Floors	2.2690667	0.115585	19.63		<.0001*
17	Weekend Cooling Setpoint	-1.843782	0.097938	-18.83		<.0001*
15	Weekend Heating Setpoint	2.6450635	0.161988	16.33		<.0001*
6	Lighting	1.146256	0.076585	14.97		<.0001*
8	South WWR	15.924895	1.294872	12.3		<.0001*
27	Air Leakage	5.5171487	0.511073	10.8		<.0001*
10	North WWR	13.414101	1.276112	10.51		<.0001*
13	Orientation	-5.274715	0.735124	-7.18		<.0001*
18	Roof Uvalue	6.0015617	0.914363	6.56		<.0001*
9	East WWR	8.1454841	1.27158	6.41		<.0001*
12	Aspect Ratio	1.623141	0.270136	6.01		<.0001*
24	Windows U-Value	2.2927573	0.390109	5.88		<.0001*
28	South Overhang	-0.091265	0.016321	-5.59		<.0001*
4	Occupancy	176.70687	33.16556	5.33		<.0001*
21	Wall U-Value	4.9363411	0.993007	4.97		<.0001*
11	West WWR	5.7833139	1.287682	4.49		<.0001*
34	West Overhang	-0.051785	0.016953	-3.05		0.0023*
2	Floor Height	7.2709808	2.825663	2.57		0.0101*
22	Wall Absorption	7.0299778	3.205696	2.19		0.0284*
7	DHW	0.2398929	0.128754	1.86		0.0626
19	Roof Absorption	5.4887613	3.170761	1.73		0.0836
33	North Fin	0.0234081	0.0165	1.42		0.1561
32	North Overhang	-0.019963	0.016572	-1.2		0.2285
20	Roof Emissivity	1.5623407	2.646349	0.59		0.555
23	Wall Emissivity	6.8930586	18.62458	0.37		0.7113
30	EastOverhang	0.0032346	0.016654	0.19		0.846
31	East Fin	0.0025568	0.016543	0.15		0.8772
35	West Fin	-0.001751	0.016853	-0.1		0.9173
29	South Fin	0.0005138	0.016525	0.03		0.9752

Table 4.6 CS4_Miami sensitivity analysis result

CS4-Miami:Mid Office in Miami						
Variable No.	**Variable**	**Estimate**	**Std Error**	**t Ratio**	**t Ratio**	**Prob>|t|**
5	Appliance	1.6444253	0.034257	48		<.0001*
1	Gross Floor Area	1122.6649	23.60788	47.55		<.0001*
16	Weekdays Cooling Setpoint	-6.512386	0.149089	-43.68		<.0001*
26	Windows SHGC	62.834844	1.456182	43.15		<.0001*
17	Weekend Cooling Setpoint	-2.434205	0.089578	-27.17		<.0001*
6	Lighting	1.7018393	0.068473	24.85		<.0001*
3	Number of Floors	1.8218332	0.107625	16.93		<.0001*
8	South WWR	18.152872	1.181504	15.36		<.0001*
10	North WWR	14.738753	1.149423	12.82		<.0001*
14	Weekdays Heating Setpoint	1.8296541	0.147012	12.45		<.0001*
13	Orientation	-7.035161	0.679392	-10.36		<.0001*
9	East WWR	8.9119795	1.177767	7.57		<.0001*
15	Weekend Heating Setpoint	1.0294045	0.148947	6.91		<.0001*
11	West WWR	8.0031026	1.17149	6.83		<.0001*
4	Occupancy	185.73906	29.80625	6.23		<.0001*
12	Aspect Ratio	1.4766951	0.246791	5.98		<.0001*
28	South Overhang	-0.08703	0.015199	-5.73		<.0001*
21	Wall U-Value	4.4514518	0.896444	4.97		<.0001*
27	Air Leakage	2.1461955	0.470878	4.56		<.0001*
18	Roof Uvalue	3.4280667	0.835605	4.1		<.0001*
32	North Overhang	-0.049547	0.015239	-3.25		0.0012*
2	Floor Height	8.3151452	2.600231	3.2		0.0014*
7	DHW	0.2933246	0.118166	2.48		0.0131
30	EastOverhang	-0.037525	0.015281	-2.46		0.0141
22	Wall Absorption	7.0229188	2.987882	2.35		0.0188
35	West Fin	-0.030488	0.015221	-2		0.0453
29	South Fin	-0.02269	0.015501	-1.46		0.1434
19	Roof Absorption	3.7524517	2.935821	1.28		0.2013
35	West Fin	0.0134566	0.015559	0.86		0.3872
31	East Fin	-0.01239	0.014982	-0.83		0.4083
33	North Fin	-0.00865	0.015505	-0.56		0.577
24	Windows U-Value	-0.118674	0.357813	-0.33		0.7402
20	Roof Emissivity	-0.755822	2.382659	-0.32		0.7511
23	Wall Emissivity	4.4418316	16.76223	0.26		0.791

4.2.1.3. Variable Selection and Linear Regression Model

After implementing the sensitivity analysis, we are going to create regression models out of the whole design space experiment, which should be started from variable selection out of all variable considered. The goal of variable selection in regression analysis is to identify the smallest subset of the covariates, in this case, the building parameters, for the regression model. Our strategy is the *best subset regression*, which applies a model selection criterion to all possible subsets and selects the subset (which corresponds to a regression model) with the highest adjusted R^2; such a criterion and its definition is discussed later in this section. After selecting the most significant parameters, a linear relationship between a response y and a covariate x can be expressed in terms of the following model:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon \qquad \text{Eq. (4.7)}$$

where ε is the random part of the model which is assumed to be normally distributed with mean 0 and variance σ^2, that is, $\varepsilon \sim N(0, \sigma^2)$; because ε is normally distributed, so is y with mean $E(y) = \beta_0 + \beta_1 x_1 + .. + \beta_k x_k$ and $Var(y) = \sigma^2$. The unknown parameters in the model are the regression coefficients and the error variance σ^2. Thus the purpose for collecting the data is to estimate and make inference about these parameters.

If N iterations in each performance simulation are collected, (2,000 iterations in each case studies), the model for them can take a linear regression model as:

$$y_i = \beta_0 + \beta_1 x_{i,1} + \beta_2 x_{i,2} + \cdots + \beta_k x_{i,k} + \varepsilon_i, \quad i = 1,2, \ldots, N = 2000 \qquad \text{Eq. (4.8)}$$

If $\hat{y}_i$ is the fitted value for y_i, the quantity $e_i = y_i - \hat{y}_i$, is called residuals. Clearly, the ith residual denotes the difference between the observed response y_i and the fitted value $\hat{y}_i$. The sum of squares of the residuals, also called the residual sum of squares (RSS), is given by

$$RSS = \sum_{i=1}^{N} e_i^2 = \sum_{i=1}^{N} (y_i - \hat{y}_i)^2, \qquad \text{Eq. (4.9)}$$

and the mean square error is given by $MSE = \frac{RSS}{N-2}$, where N-2 is the degree of freedom associated with RSS.

It is necessary to understand the relationship between residual, e, and the variance of the regression model error, σ^2. It has been shown and proven that $E(RSS) = (N-2)\sigma^2$, and therefore, MSE is an unbiased estimator of σ^2 (Wu and Hamada 2011)

$$\mathrm{E(MSE)} = \sigma^2 \quad \text{Eq. (4.10)}$$

$$\frac{E(\sum_{i=1}^{N} e_i^2)}{N-2} = \sigma^2$$

Residuals are very useful in judging the appropriateness of a given regression model with respect to the available data. There are two terms used to evaluate the appropriateness of a regression model base on the residuals: R^2 and $adjusted\ R^2$. R^2 measures the proportion of total variation explained by the fitted regression model; a higher R^2 value indicates a better fit of the regression model. A good model selection criterion should consider good model fitting as well as penalize model complexity (Wu and Hamada 2011). In models where the number of covariates increases, R^2 might not be a suitable criterion because in increases as the number of covariates increases. An alternative criterion is the adjusted R^2, which takes into consideration the reduction in degree of freedom for estimating the residual variance with inclusion of covariance in the model.

Four linear regression models have been developed for the case studies. To evaluate the effectiveness of a linear regression model, we check adjusted R^2 and the residuals. Table 4.7 shows R^2, adjusted R^2 and root mean square error (RMSE). The adjusted R^2 of 90.8% for Chicago case study, for example, is the highest R^2 that can be achieved using all 20 variables, meaning that 90.8% of the total variance can be explained by the regression model constructed by these variables. These values are based on the highlighted variables in each case study. Adding any additional variables would reduce the adjusted R2 value. In all four cases, the regression fitted model can explain at least 84.7 percent of the total variance, which sufficiently reflects the overall distribution as well as individual sample values of the normal building energy model. The values of root mean square error (RMSE) are not suggesting the goodness of the fitted model, but will be considered in the calculation of the desired performance, in the following section. Once again it should be noted that thermal load means the sum of cooling and heating load.

Table 4.7 Results of developing linear regression models for four cases

Case Study	***RSquare***	***RSquare Adj***	***RMSE***
CS1-Chicago	0.908	0.906	11.186
CS2-LA	0.858	0.855	19.461
CS3-Atlanta	0.853	0.85	16.321
CS4-Miami	0.847	0.845	14.931

Another measures of goodness of fit that is used to summarize the discrepancy between observed values and the values expected are to test the normality of residuals. Figures 4.2 to 4.5 plots the histograms of the actual simulated and fitted data, the actual by predicted plot, the histogram of residuals, and the residual by row plots for each case respectively. From these plots, we can find that the spreads of the residuals are distributed around zero, and approximately form a normal distribution, which validate the regression models. Table 4.8 shows the summary of these graphs values.

Table 4.8 Summary of the fitted regression model versus actual building energy model from EPC

<table>
<tr><th colspan="2">Case Study</th><th>Min Thermal Laod</th><th>Max Thermal Load</th><th>Mean Value</th><th>Std Dev</th><th>Predicted vs Actual Residual Location</th><th>Predicted vs Actual Residual Dispersion</th></tr>
<tr><td rowspan="2">CS1-Chicago</td><td>Simulated</td><td>75.85</td><td>795.29</td><td>222.23</td><td>86.43</td><td rowspan="2">-9.20E-14</td><td rowspan="2">11.186</td></tr>
<tr><td>Fitted</td><td>78.28</td><td>800.88</td><td>221.18</td><td>85.37</td></tr>
<tr><td rowspan="2">CS2-LA</td><td>Simulated</td><td>14.37</td><td>576.57</td><td>155.26</td><td>81.79</td><td rowspan="2">1.24E-13</td><td rowspan="2">19.46</td></tr>
<tr><td>Fitted</td><td>35.5</td><td>586.9</td><td>153.2</td><td>78.42</td></tr>
<tr><td rowspan="2">CS3-Atlanta</td><td>Simulated</td><td>36.81</td><td>774.06</td><td>155.70</td><td>75.46</td><td rowspan="2">-4.96E-14</td><td rowspan="2">16.32158</td></tr>
<tr><td>Fitted</td><td>43.66</td><td>628.39</td><td>153.49</td><td>67.61</td></tr>
<tr><td rowspan="2">CS4-Miami</td><td>Simulated</td><td>45.3</td><td>1143.4</td><td>189.96</td><td>82.11</td><td rowspan="2">5.40E-14</td><td rowspan="2">14.931</td></tr>
<tr><td>Fitted</td><td>65.04</td><td>1041.39</td><td>187.89</td><td>73.9</td></tr>
</table>

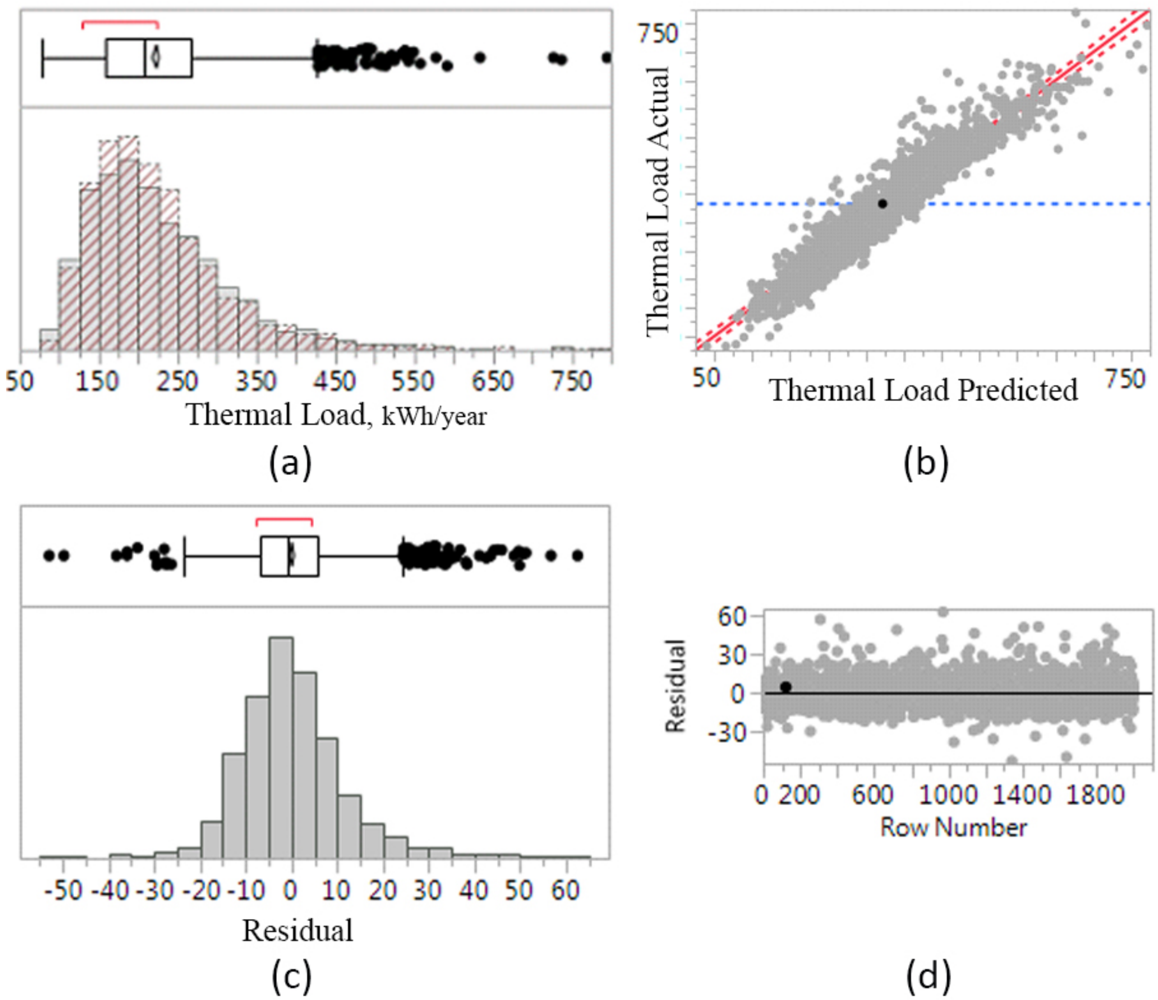


Figure 4.2 CS1_Chicago, fitted regression model verification: (a) distributions of the actual simulated and fitted data, black continuous lines are actual data and the dashed red lines are fitted data; (b) actual versus predicted plot, (c) histogram of residuals, and (d) residual by row plots

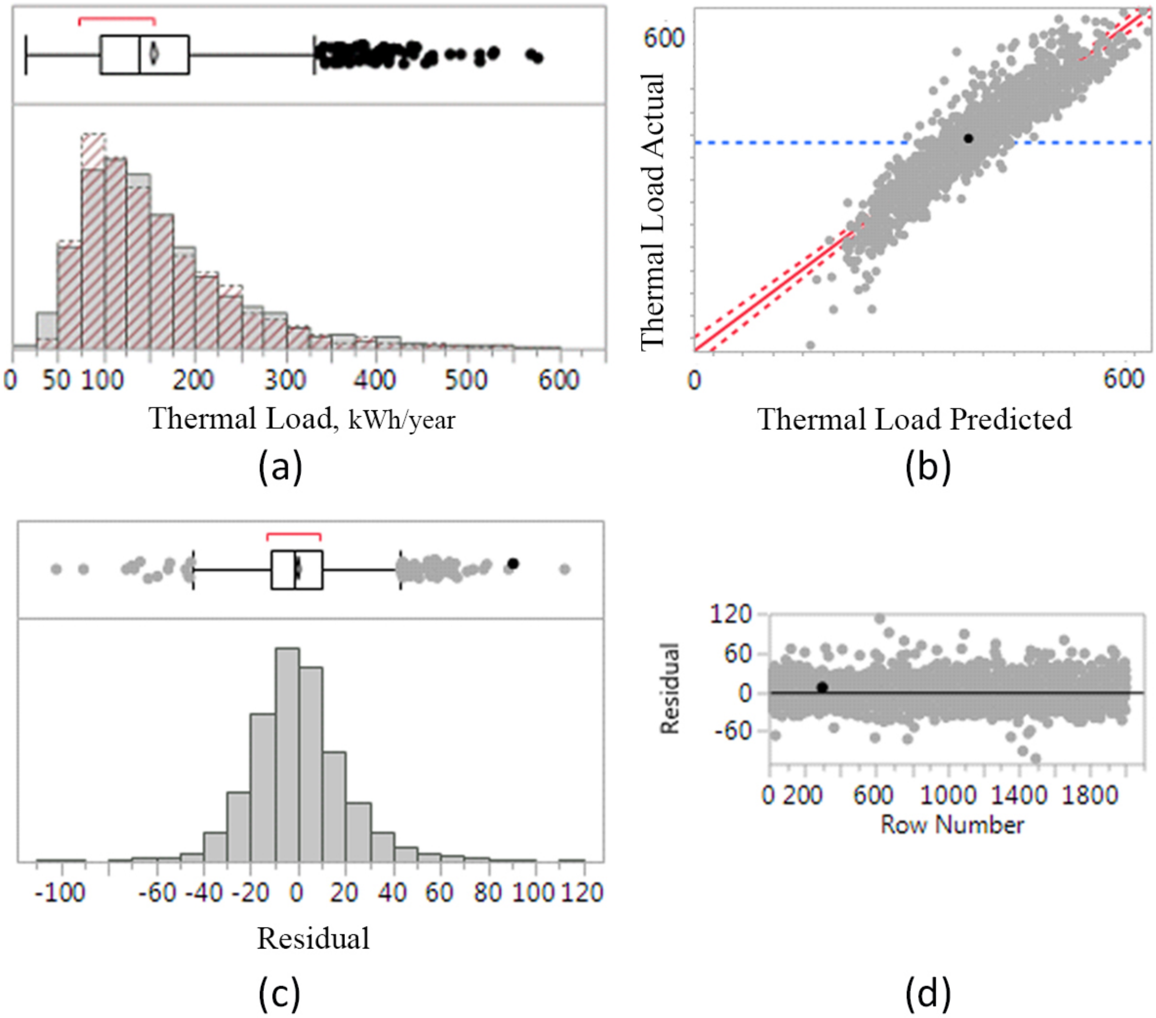


Figure 4.3 CS2_LA, fitted regression model verification: (a) distributions of the actual simulated and fitted data, black continuous lines are actual data and the dashed red lines are fitted data; (b) actual versus predicted plot, (c) histogram of residuals, and (d) residual by row plots

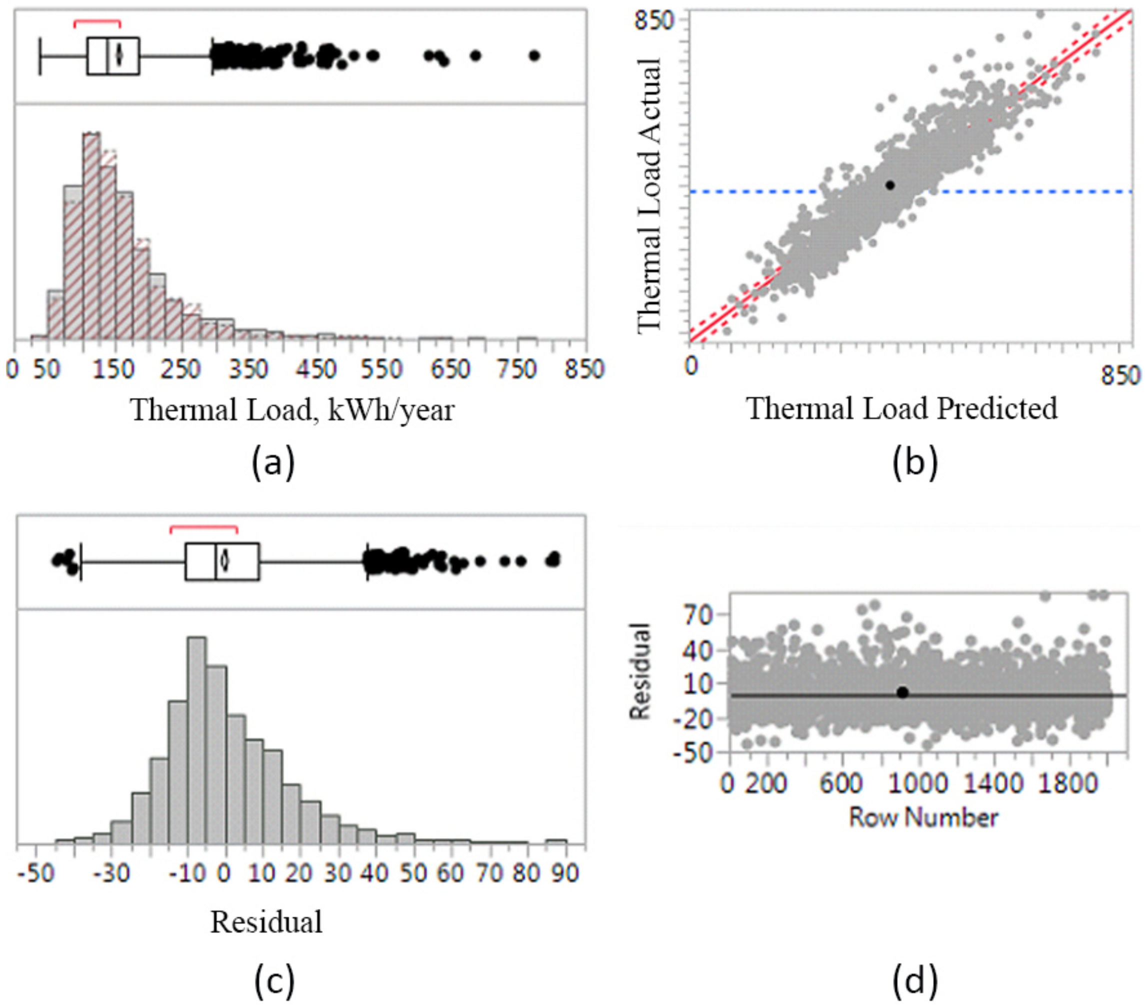


Figure 4.4 CS3_Atlanta, fitted regression model verification: (a) distributions of the actual simulated and fitted data, black continuous lines are actual data and the dashed red lines are fitted data; (b) actual versus predicted plot, (c) histogram of residuals, and (d) residual by row plots

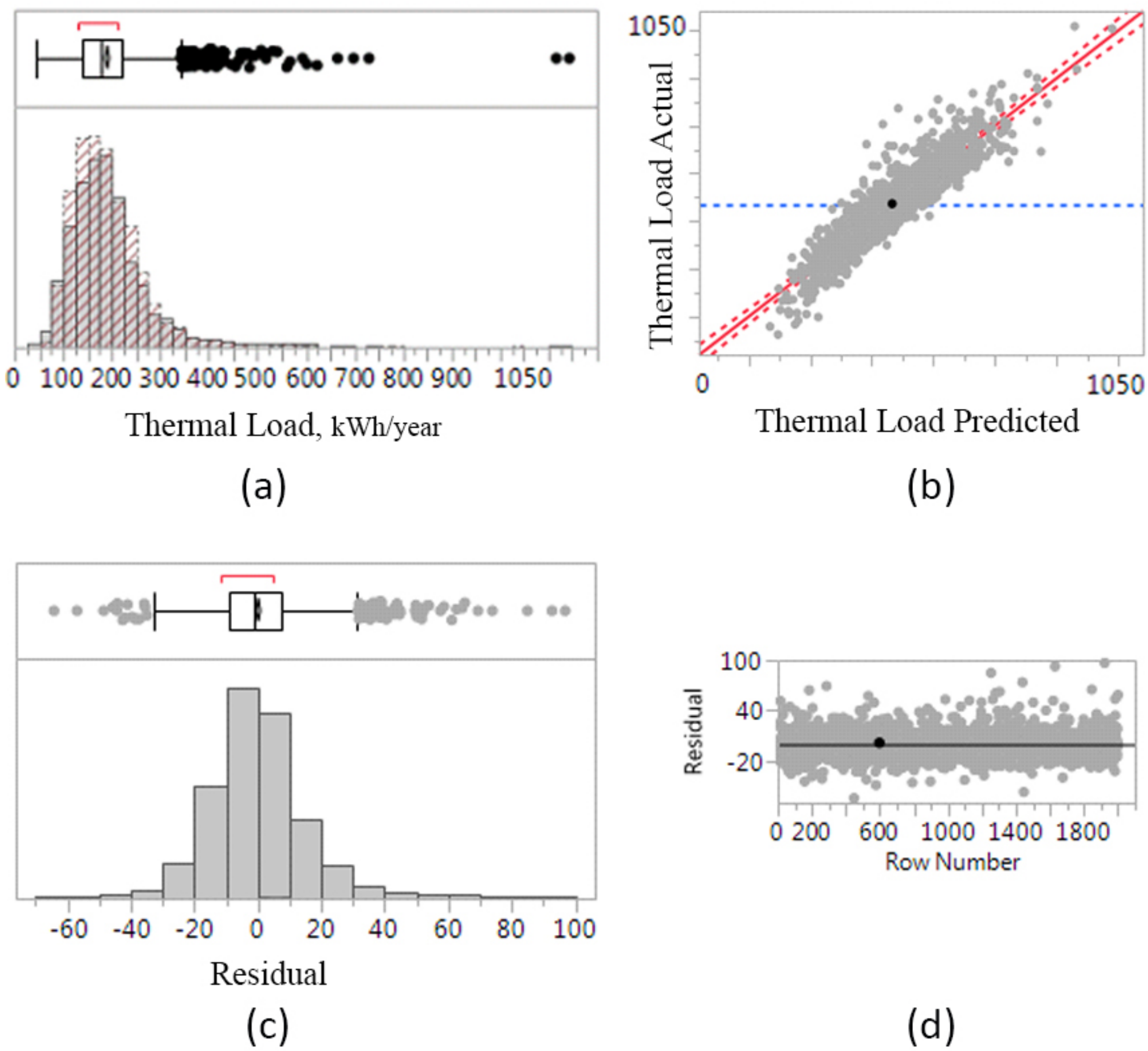


Figure 4.5 CS4_Miami, fitted regression model verification: (a) distributions of the actual simulated and fitted data, black continuous lines are actual data and the dashed red lines are fitted data; (b) actual versus predicted plot, (c) histogram of residuals, and (d) residual by row plots

4.2.2. Elicitation of the Performance Objective:

A review of the appropriate normative decision theory literature, for example (Keeney and Raiffa 1993) for preference elicitation as well as (Abbas and Matheson 2004) for probabilistic representation, suggests us that we can represent our preferred performance $P(y)$ probabilistically as a probability distribution function (PDF). But the way this performance distribution function is quantified and depicted is our next concern.

In the previous section, in the process of implementing uncertainty and sensitivity analysis for a building design scenario, we have come up with a probability distribution of the output, thermal load, representing all possible energy performance and their distribution for that particular design scenario, called response space (Figure 4.2(a) to 4.5(a)). We would like to choose a subset of the aforementioned distribution that represents our preferred energy performance to be achieved (Figure 4.6). For instance, the objective can be expressed as a designer's preference to have thermal demand equal or less than b=100 W/m2/year, based on its range for elementary school building in Chicago.

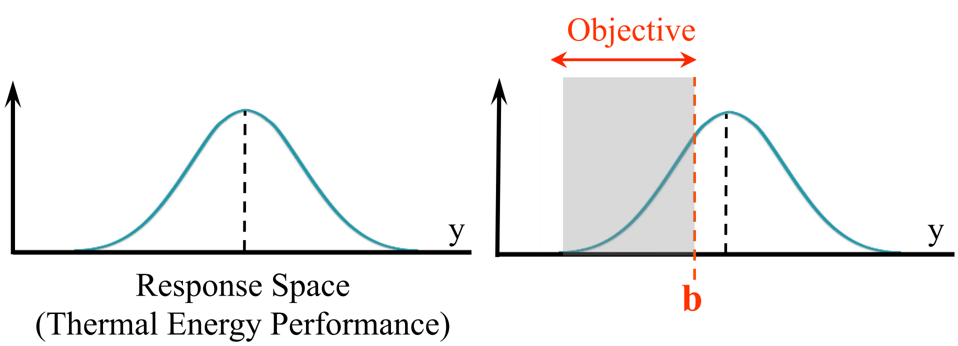


Figure 4.6 defining the "preferred performance" out of the total solution space

These distributions along with the subset of the distribution are used in linear inverse modeling. LIM uses regression model and calculated fitted value out of thermal energy performance, $\hat{y}_i$, to estimate design parameters. As mentioned before, $\hat{y}_i$ is a random number normally distributed with variance σ^2. Although the fitted value has shown to have a good fit with the actual result of the normative model, there are still some errors, associated with residual, in using this reduced regression model. In order to minimize the associated error and consider the probabilistic nature of the prediction process, we define the energy performance objective probabilistically. As an example, preferences on thermal loads can be expressed as a desire to have a 90% chance of being below b=100 W/m2/year; this means shifting the mean value to a lower energy performance while the whole new range is covered by the statistical model profile. As depicted in figure 4.7, the objective, b, is a random number with a distribution represented as a dashed line in orange color. Based on the preferred level of confidence in fulfilling energy objective, we will move the value of b to a lower level as b' by applying the concept of confidence and prediction interval for the energy performance calculation, as described in the following section.

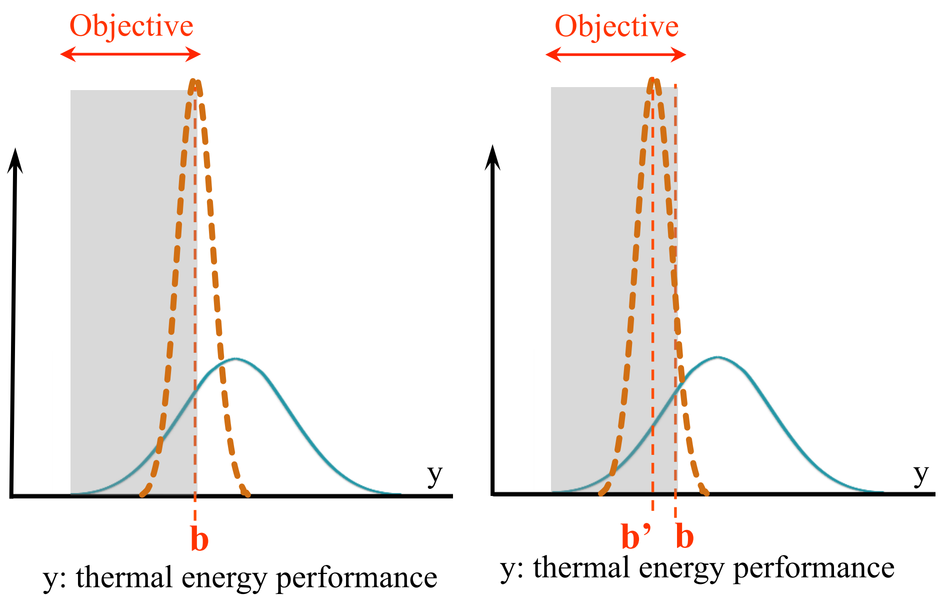


Figure 4.7 Shifting the desired thermal energy performance to a lower value in the inverse modeling calculation; the left image shows considering b without incorporating confidence level (corresponds to 50% confidence), and the image on right shows when we apply higher confidence than 50%

4.2.2.1. Confidence and Prediction interval

Consider the prediction of a new or future performance y corresponding to $\boldsymbol{x} = \boldsymbol{x_0}$. We assume that the multiple linear regression model developed from the sampled data will be appropriate for the new objective performance. Therefore, the predicted value $\hat{y}_{pred,\boldsymbol{x_0}}$ is still obtained by substituting $\boldsymbol{x} = \boldsymbol{x_0}$ in the fitted regression model and is the same as the estimated mean response $\hat{y}_{\boldsymbol{x_0}}$. The $100(1-\alpha)\%$ confidence interval for a predicted individual response corresponding to $\boldsymbol{x} = \boldsymbol{x_0}$, also called a $100(1-\alpha)\%$ prediction interval is given by

$$\hat{y}_{pred,\boldsymbol{x_0}} \pm t_{\frac{\alpha}{2},N-k-1} s \sqrt{1 + \frac{1}{n} + \frac{(x_0 - \bar{x})^2}{\sum_{i=1}^{n}(x_0 - \bar{x})^2}} \qquad \text{Eq. (4.11)}$$

where $t_{\frac{\alpha}{2},n-2}$ is the upper $\frac{\alpha}{2}$ point of t distribution with $n-2$ degree of freedom, as shown in figure 4.8.

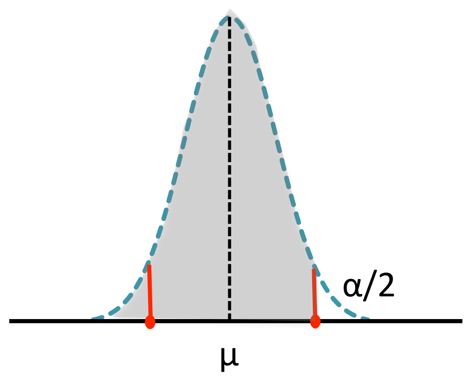


Figure 4.8 $\mathbf{100(1-\alpha)}$% confidence interval

Suppose we would like to have $100(1-\alpha)\%$ confidence that the response is less than b. We have to find all $\boldsymbol{x_0}$s whose estimated $\hat{y}_{pred,\boldsymbol{x_0}}$ is less than b. In other words,

$$\hat{y}_{pred,\boldsymbol{x_0}} + t_{\frac{\alpha}{2},N-k-1} s \sqrt{1 + \frac{1}{n} + \frac{(x_0 - \bar{x})^2}{\sum_{i=1}^{n}(x_0 - \bar{x})^2}} \leq b \qquad \text{Eq. (4.12)}$$

Therefore,

$$\hat{y}_{pred,\boldsymbol{x_0}} \leq b - t_{\frac{\alpha}{2},N-k-1} s \sqrt{1 + \frac{1}{n} + \frac{(x_0 - \bar{x})^2}{\sum_{i=1}^{n}(x_0 - \bar{x})^2}} = b' \qquad \text{Eq. (4.12)}$$

As a result, we are interested in generating all possible responses (thermal demand) that is less than b' instead of b in the calculation.

Table 4.9 Upper percentile of $\boldsymbol{t}$ distribution; $\boldsymbol{\alpha}$ =upper tail probability, $\boldsymbol{\nu}$ = degree of freedom

% Confidence	50	80	85	90	95	98	99	99.4	99.8	99.9
$\boldsymbol{\alpha}$	0.250	0.100	0.075	0.050	0.025	0.010	0.005	0.003	0.001	0.0005
t for $\boldsymbol{\nu > 120}$	0.674	1.282	1.440	1.645	1.960	2.326	2.576	2.807	3.090	3.291

4.2.3. Constraints and Inequalities in Building Design Parameters

In the building design context, we define constraints over each design parameter/variable based on literature study, the design requirements, regulations, limitations, and the designers and/or stakeholders' preferences. For instance, if we design an office building in a location in which the city policy obligates the building height in that region to be less than 50 feet, and the building requirements need spaces to be distributed in at least two stories, which is 20 feet, then we define the constraint over the building height as any value between 20 1nd 50 feet, which is represented as a uniform distribution.

For any parameter that has only one value, or when a design parameter in x_i has been chosen, this parameter may be represented with a single (deterministic) number. As design is an iterative and sequential process of decision-making on design parameters, the inverse process can be performed iteratively as the knowledge about the design evolves. At the beginning of the design when most parameters are undecided, the models of constraints are at their maximum space range. After running the first iterate of the analysis, as any decision regarding a design parameter is made, that prior knowledge about that parameter will be changed to a decided deterministic value, and the inverse analysis will be performed again to see how the new decision would affect the results of the rest of undecided parameters. In other words, the prior constraint models will be updated as new data or decision accumulated. The result of each analysis iteration may suggest whether the collection of new data or making more constraints on the parameters is required for sufficiently precise parameter estimation. This co-evolution and redefinition of design space, which is derived from the dynamic nature of the design, is the foundation of creativity in design (Dorst and Cross 2001).

4.2.4. Solving A Linear Inverse Problem to Replicate Design Parameters

Based on the preferred energy performance for a particular scenario of the building use in a city, and associated linear regression model of building energy function, the next step is to drive design parameters estimation of building for that scenario. The first hypothesis can be rewritten as follow:

Given the preferred thermal energy performance of a particular type of the building in a city and a linear estimation of a building energy model, one could solve a linear inverse problem to generate distributions of the building energy model input variables, which lead to the preferred energy performance.

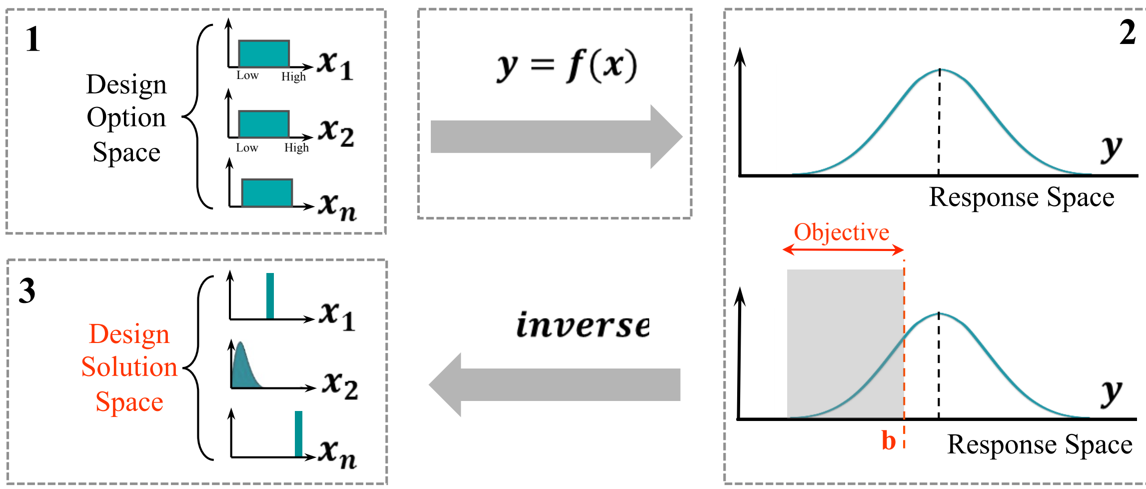


Figure 4.9 the process of going from whole design option space to produce solution space using inverse modeling approach

Figure 4.9 graphically represents the process of going from whole design option space to the solution space through inverse modeling approach. The calculation of the inverse inference is too complicated to be computed analytically with the non-linear models, but can be adequately sampled using modern computer techniques (Schmidt, George et al. 1998). The Markov Chain Monte Carlo (MCMC) random walk is used to randomly sample the underdetermined problem (using the metropolis algorithm), and select likely values given the approximate equation. The metropolis algorithm produces a series of samples whose distribution approaches an underlying target distribution. The probability distribution of the latter is assumed Gaussian, with given standard deviation (Van den Meersche, Soetaert et al. 2009). The result of the analysis can be similar to figure 4.10, showing the probability distribution on the solution space on the right for each design variables, and also the relationship between each two variables (joint distributions).

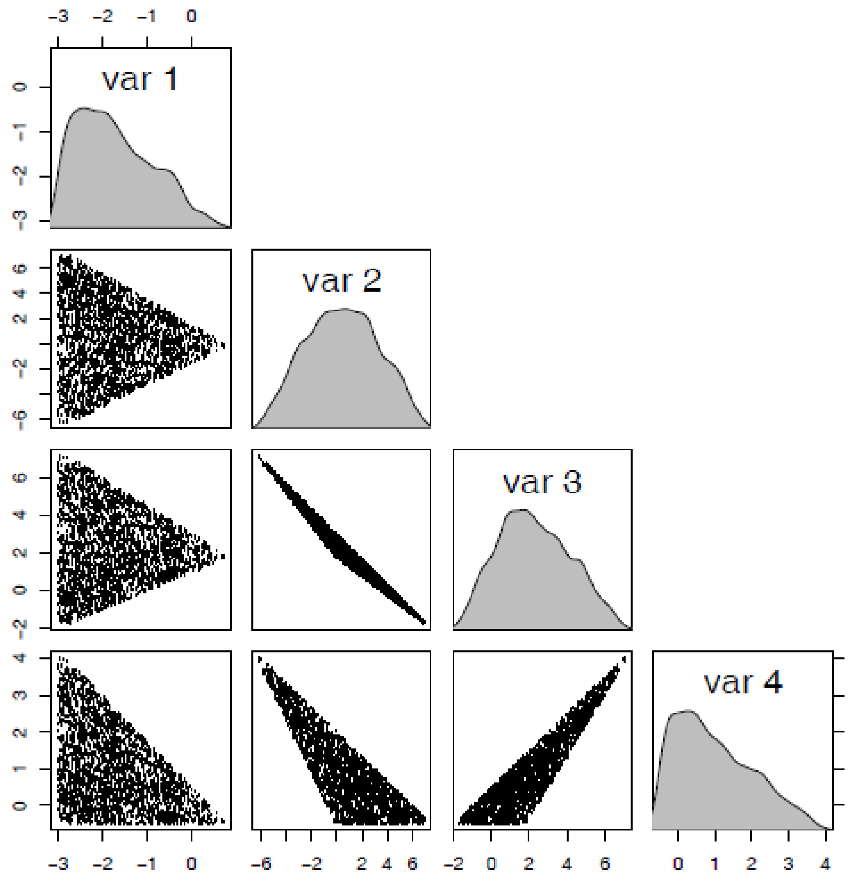


Figure 4.10 An example of the outputs of the inverse modeling, random sample of the underdetermined system including equalities and inequalities, (Van den Meersche, Soetaert et al. 2009)

The calculation will be implemented in R (Statistical Package 2009), by taking advantage of LimSolve R-Package, which uses “xsample” function to probabilistically estimate design variables through implementing linear inverse modeling (Van den Meersche, Soetaert et al. 2009). The feasible region of linear problem would be defined as the part of parameter space that contains all solutions of the reduced problem.

4.3. REMARKS OF THE CHAPTER

At the first part of the chapter, it is proven that the thermal energy demand in a particular operation-and-climate condition of buildings can be expressed as a linear regression model. To implement such a model, we explored a full design option space for four design scenarios using normative EPC, implemented sensitivity analysis, and came up with linear regression models representing thermal demand as a function of the most significant parameters. Such models along with any constraints on the values of building design variables and the objective energy performance are used in linear inverse models. Outputs of inverse modeling for design parameters represent the estimation of each design parameters probabilistically given the objective.

In the linear inverse modeling, therefore, rather than calculating a single "best" solution for parameters x_i according to some criterion, we can produce a large number of "likely" solutions, that both fit the data and any other objective that is used. The result inference, shown as distributions, provides a means of estimating the likelihood of properties of parameters from preferred objective and explicitly emphasizes the multiple solutions that can account for the design problem. The range of the different likely results fits well with the goal of the design, as mentioned before, to gives a designer the freedom to choose among feasible options that have a high likelihood of meeting objectives. Such a method can be a good candidate to limit and form the design option space and represent feasible solutions in order to help designers in their decision making process.

CHAPTER 5

ANALYSIS OF THE FEASIBILITY OF THE PROPOSED APPROACH TO EARLY DESIGN CASE STUDIES

Four design cases are chosen, representing two different types of the buildings, each in two different climate zones as follows:

Table 5.1 lists of early design decision case studies

Building Type	Elementary School		Mid-rise Office	
Location	Chicago	Los Angeles	Atlanta	Miami
Climate Zone	5A	3B	3A	1A
Case Study	CS1-Chicago	CS2-LA	CS3-Atlanta	CS4-Miami

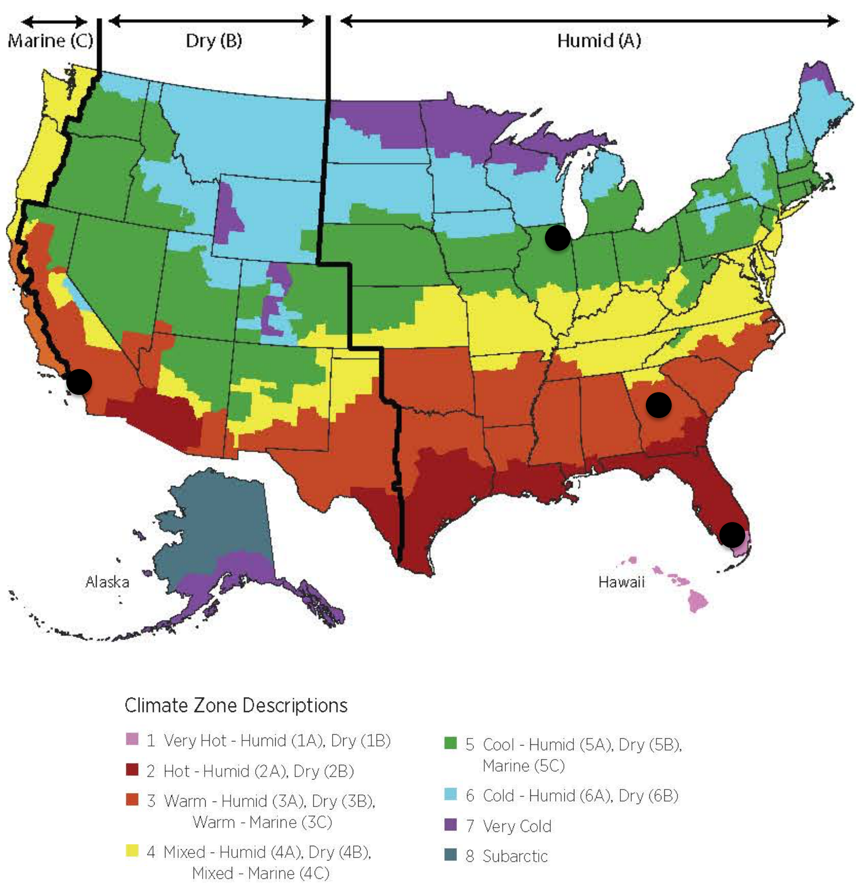


Figure 5.1 Climate Zone map, based on ASHRAE 90.1, and location of case studies

For each design case, three performance objectives are explored at the first stage. We define objective as the thermal load (sum of cooling and heating load) to be equal or less than a particular value, b; to be coherent in all of the four case studies, these three values are the 0.7, 0.4, and 0.1 percentiles of the response space (all possible energy performance for that case study), representing a conservative, intermediate, and strict objective energy performance respectively.

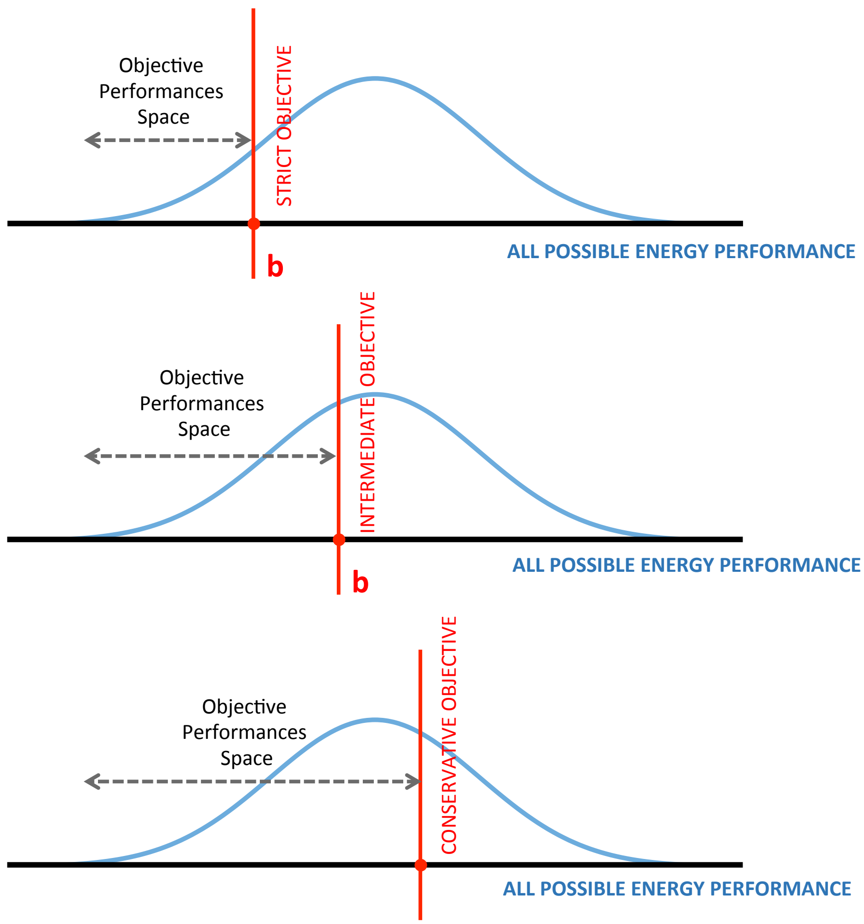


Figure 5.2 Defining three levels of energy performance objectives as strict, intermediate, and conservative ones, calculated at 10, 40 and 70 percentiles of the whole response spaces in each design case

Considering the error in predicting the objective, which is the result of using the fitted regression model in the inverse approach, we try reducing this error by defining 90 % confidence ($\alpha = 0.1$) that the total load is less than b, and we generate all possible responses (thermal demand) that fulfill the following equation, as described in chapter 4.2.2.1.

$$\hat{y}_{predicted} \leq b - t \times (RMSE) \qquad \text{Eq. (5.1)}$$

Table 5.2 summarizes three aforementioned performance objectives for four design case studies, as well as the values of these objectives after the 90% confidence is considered.

Table 5.2 Performance objectives for four scenarios before and after the 90% confidence is considered; the values are thermal load, in units of kWh/m2/year

OBJECTIVE	Building Type	Elementary School		Mid-rise Office	
	Location	Chicago	Los Angeles	Atlanta	Miami
	Case Study	CS1-Chicago	CS2-LA	CS3-Atlanta	CS4-Miami
Objective before reducing error	70% percentile	253.77	177.92	171.07	210.16
	40% percentile	186.80	120.35	124.35	162.82
	10% percentile	130.10	72.28	85.34	108.51
Subtracting regression error	alpha	1.28	1.28	1.28	1.28
	Root Mean Square Error	11.19	19.46	16.32	14.93
Objective after reducing error	70% percentile with 90% confidence	219.87	138.63	138.78	173.56
	40% percentile with 90% confidence	161.84	93.78	100.87	134.45
	10% percentile with 90% confidence	112.72	56.32	69.23	89.60

The second chapter of the dissertation emphasized the need for having an approach open to iteration in performance-based decision-making that is compatible with the iterative nature of the building design. As a new decision about any parameter is made, the decided parameter is assigned a single deterministic value; the inverse analysis will be performed again, and the updated distributions for undecided parameters given the decided parameters are presented.

For more comprehensive exploration and better comparison, the implementation of the proposed inverse method in the four case studies have a coherent structure, based on the performance objectives, projects' assumed constraints, and the iterative decisions of the design parameters. We name a scenario of decision making for each case study as $CS\_i\_j\_k$, CS shows the current case study, i defines the objective, j refers to the alternatives considering constraints, and k represents the stage of iteration. At the first stage in all case studies, we start with exploring three defined objectives, called CS_1, CS_2, and CS_3. The designer chooses one of them based on the projects' objective, for instance CS_2, if he wants to have the energy performance to be less than 40% percentiles of the whole response space; the designer will assign constraints on some of the design parameters at the second stage. Here he/she explores three design alternatives as CS_2_1, CS_2_2, and CS_2_3, and tests them to select one, for example the third alternative, CS_2_3. At the third stage, designer decides on the rest of the parameters, until $CS\_2\_3\_4$ is finalized.

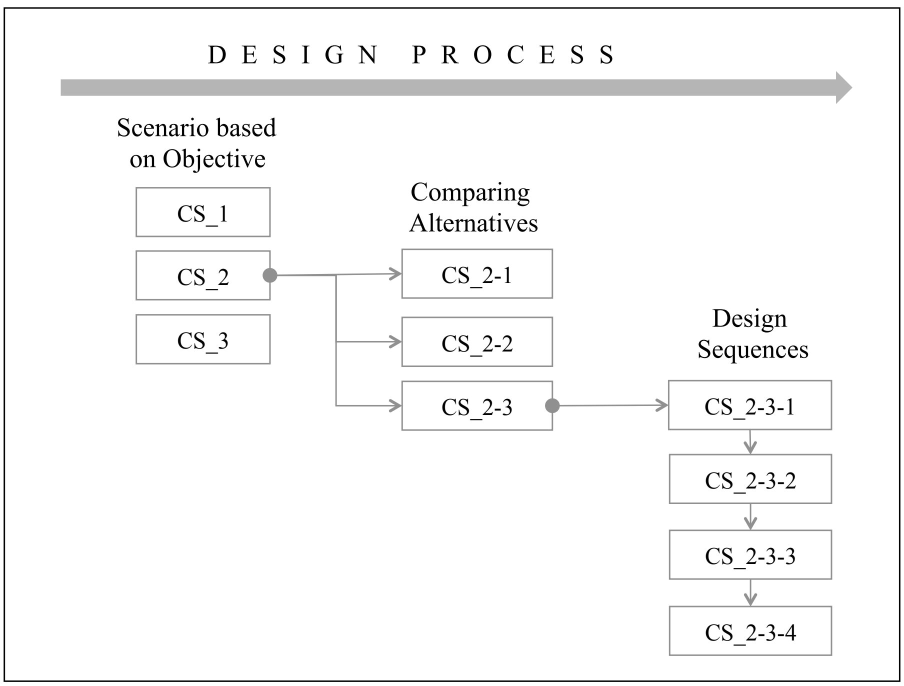


Figure 5.3 the structure of the case studies scenarios

In all of the following case studies, we go with CS_3, in which a stricter objective is considered for thermal energy performance. We expect from this exercise to gradually have a more limited design space as we gradually make decisions about each design parameters. Figure 5.4 shows the process of sequential decision making using inverse modeling.

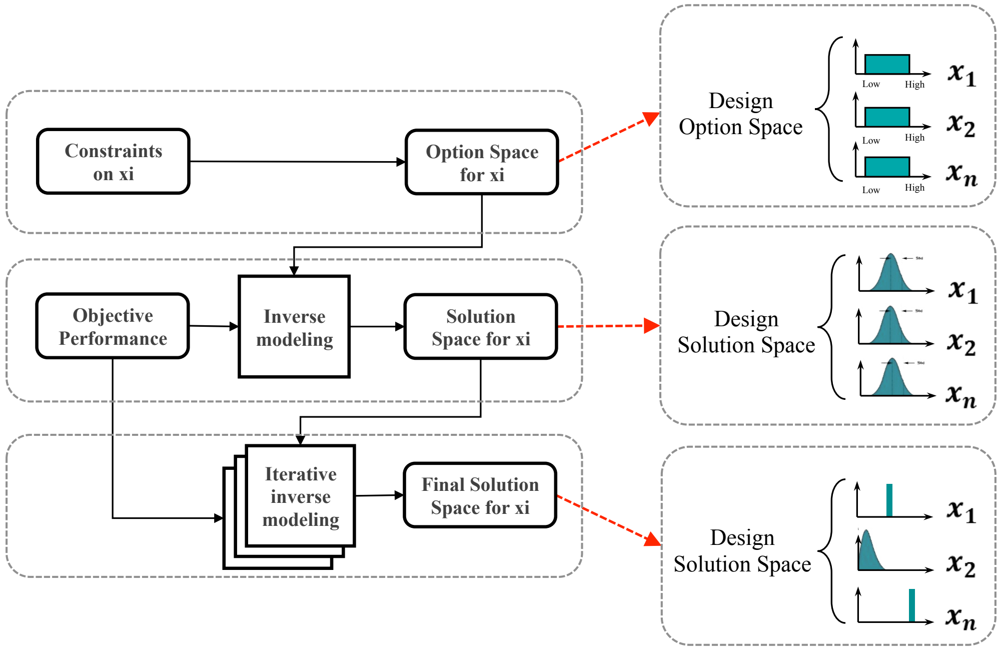


Figure 5.4 The process of sequential decision-making using inverse modeling

5.1. DESIGN OF ELEMENTARY SCHOOL IN CHICAGO

Figure 5.5 Modular school building in Chicago; designed by Perkins+Will

The first case study is a modular classroom for growing schools and communities, designed by Perkins+Will, and the goal is to have a high-performance space to enhance learning and features lower energy consumption. First, the design team explores the design option space by defining the energy performance objective to be less than any of three values of 70 percentile, 40 percentile and 10 percentile of the whole response space. Figure 5.6 depicts the histogram of thermal load for school buildings in Chicago, along with three objectives defined in the graph, and the values are listed in table 5.3. Table 5.4 shows the scenarios we will explore for this case study.

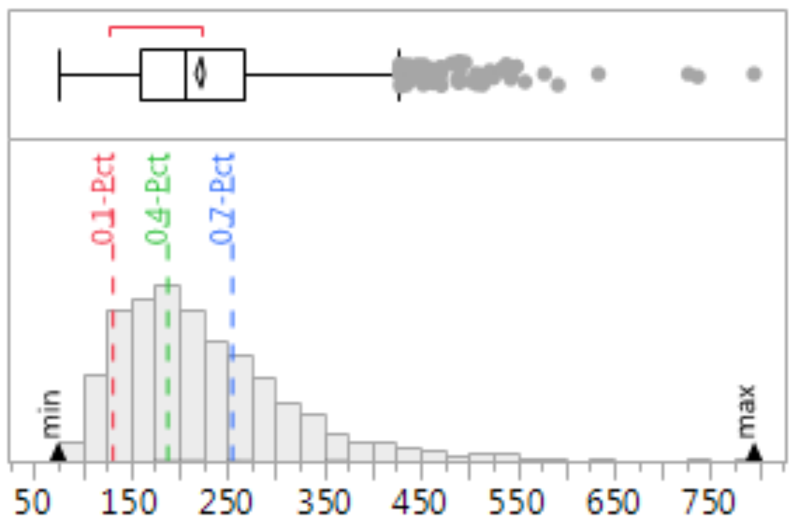


Figure 5.6 Histogram of thermal energy performance for school buildings in Chicago

Table 5.3 Thermal performance possibilities for school buildings in Chicago

Case Study	***Min***	***10 percentile***	***40 percentile***	***70 percentile***	***Max***
CS1-Chicago	75.85	130.097	186.798	253.768	795.29

Table 5.4 design scenarios for the case study of Chicago elementary school

STEP I		**STEP II**			**STEP III**	
Scenario	**Objective**	**Scenario**	**Constraints**	**Alternatives**	**Scenario**	**Iterative process of making decision**
Chicago_1	Thermal load<=253.76					
Chicago_2	Thermal load<=186.79					
Chicago_3	Thermal load<=130.09					
		Chicago_3-1	Floor area=558, #floor=1	SWWR=0.2		
		Chicago_3-2	Floor area=558, #floor=1	SWWR=0.6		
		Chicago_3-3	Floor area=558, #floor=1	SWWR=1.0		
					Chicago_3-3-1	Setpoints=(21, 16, 24, 28), Occupancy=6
					Chicago_3-3-2	AirLeakage=1.1, AR=2.5, Appliance=10
					Chicago_3-3-3	EWWR=0.2, NWWR=0.35, WWR=0.5,
					Chicago_3-3-4	F_Height=4, Wall-UValue=0.5, Window-UValue=1.5, SHGC=0.1

The results of the first sets of inverse analysis for three objectives (scenarios of Chicago_1, Chicago_2, and Chicago_3) can be found in in figures 5.7(a) to (c), which shows the distributions of the most significant design variables. Due to the interdependencies of parameters, at the beginning of the process, designers cannot make any concrete decisions looking at these distributions.

The project is planning to design four modular one-story building with the floor area of 558 square meters in the site. Due to the characteristic of the site and their tendency to have the most view towards the green area on south, the design team start from exploring three alternatives for the south windows to wall ratio to investigate how different sizes of transparent areas in south would affect the decision about the rest of the parameters, and if they can have the largest possible south glazing to increase the quality of learning. Three options for south windows to wall ratio to be explored are 20%, 60%, and 100% (scenarios of Chicago_3-1, Chicago_3-2, and Chicago_3-3). Figures 5.7(d) to (f) shows the results of these design options exploration.

Based on the graphs, one finds the differences between options negligible, and feels comfortable going with the largest possible south glazing façade while having confidence of being bounded to the energy performance objective. After choosing design scenario Chicago_3-3, and getting more information about the non-design variables such as the number of students in the space, cooling and heating setpoints, and the estimated appliances uses, the design team assigns these variables a fixed value, runs the inverse modeling again, and explores the possibilities for the rest of the parameters (design scenarios of Chicago_3-3-1 represented in figures 5.7(g), design scenarios of Chicago_3-3-2, represented in figures 5.6(h)).

So far, designers have the full range of possibilities for the ratio of windows to wall for north, east and west facades, as seen in the figure 5.7(h), although the graphs suggest having lower WWR, particularly for north and east facade. Designers choose the mean value of these three variables' distributions in order to increase option spaces for the remaining undecided parameter. The values of 20%, 35% and 50% have been chosen for east, north, and west consequently.

Figure 5.7(i) shows the probability distributions of the rest of the parameters including materials and south shading device after the general mass and transparent areas are designed. Looking at the distributions for wall, roof and windows U-Values suggest having lower U-Values (0.35, 0.22, and 0.96 W/m2K for wall, roof and windows respectively) as also is predictable by rules of thumb and prescriptive methods. However, due to financial limitations, the design team cannot select very low U-value for glazing, as suggested by mean value, and they investigate the possibility of having higher glass thermal conductivity (while it should be in the range of parameter solution space), and compensating that with the remaining parameters.

After trying different values for glazing U-Value and SHGC, some of which resulted in zero solution, the design team came up with the values for these parameters, which produce solution while they are not as low as the suggested mean value. You can find those values in table 5.4 (scenario of Chicago_3-3-4), and the associated inverse modeling results is shown in figure 5.7(j). As seen, the graph suggests values for south shading factor to be 0 and roof U-Value to be less than 0.2 W/m2K in order to comply with initial energy performance objective.

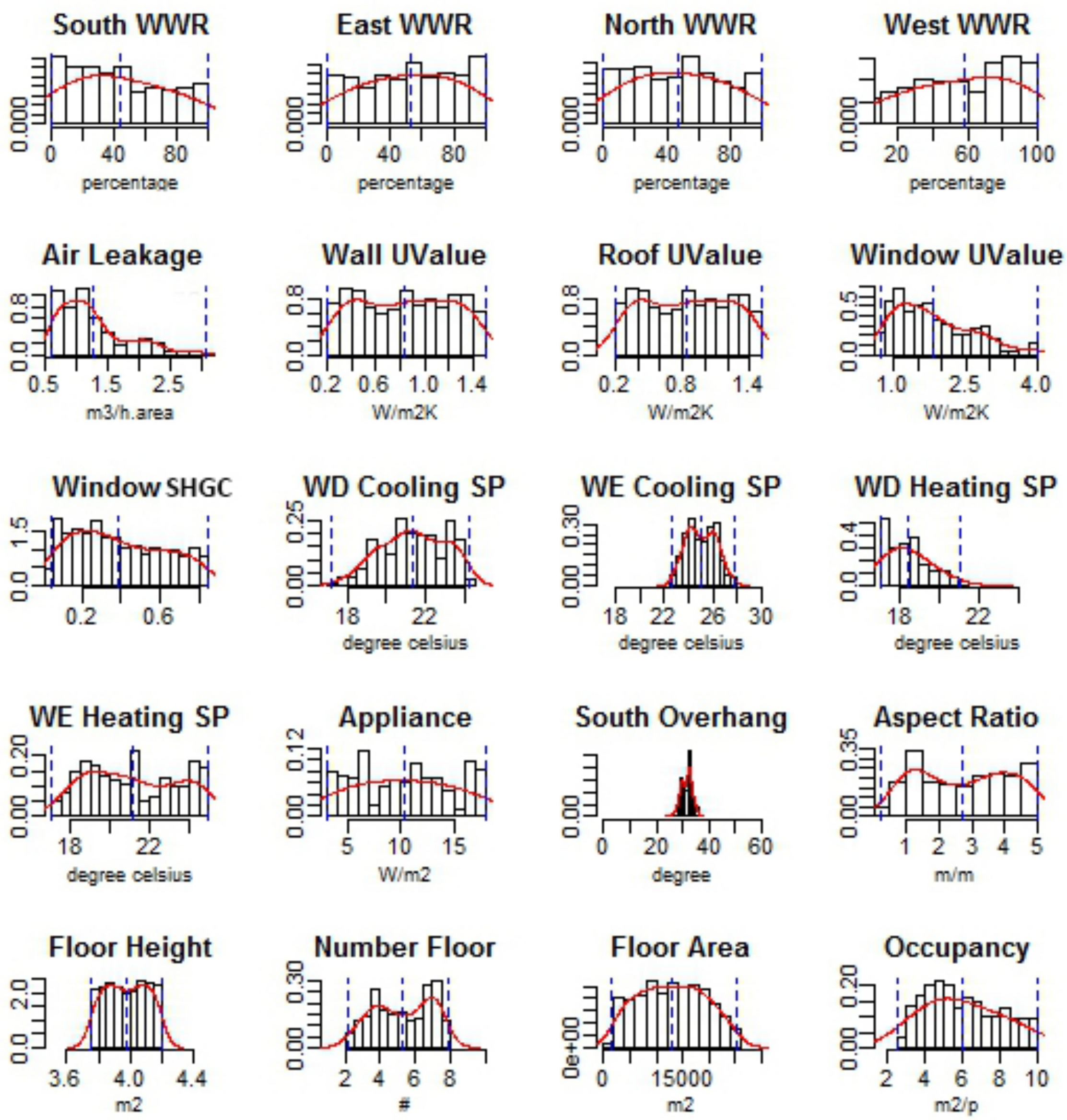


Figure 5.7(a) Chicago case study; design scenario Chicago_1

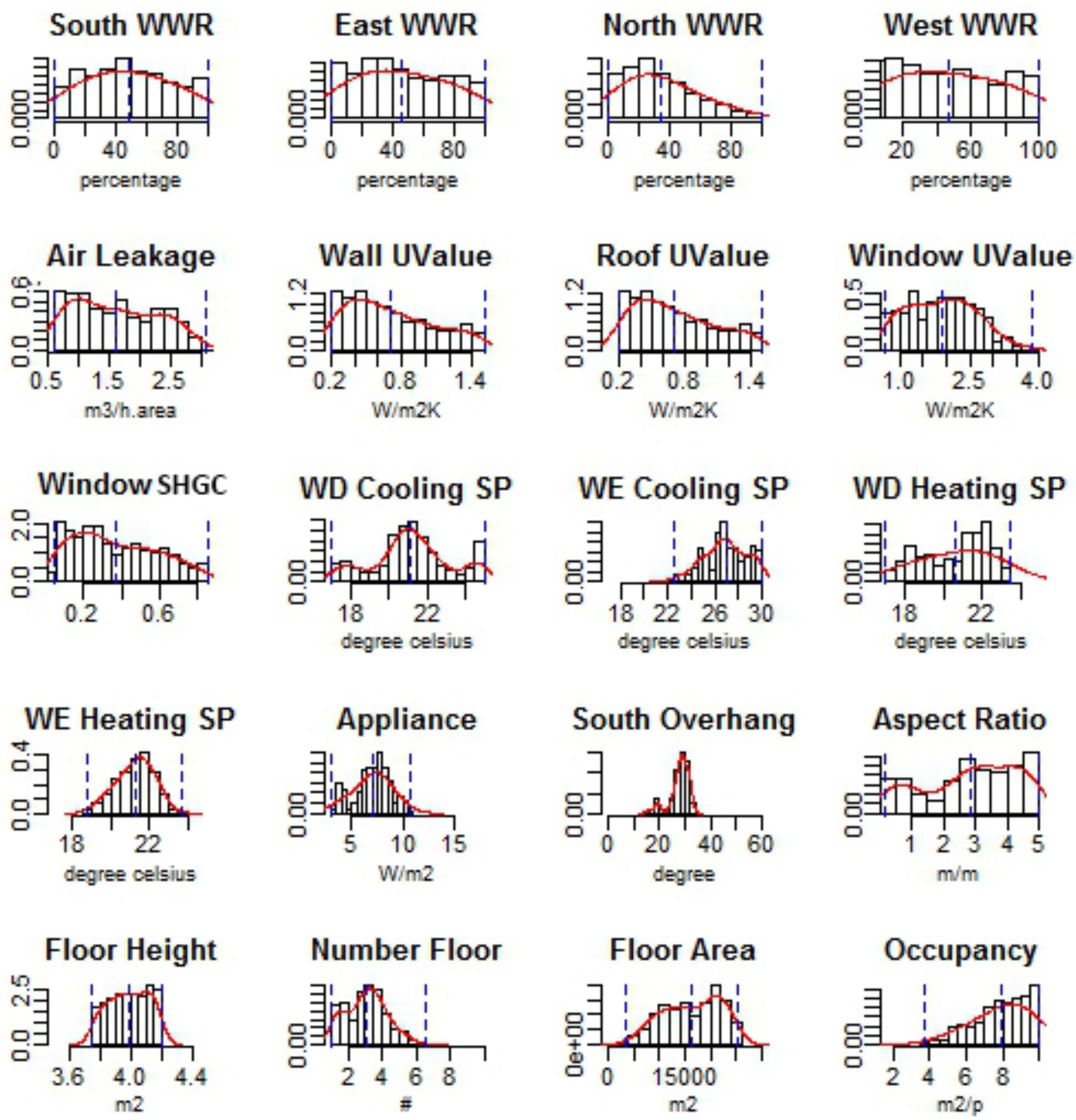


Figure 5.7(b) Chicago case study; design scenario Chicago _2

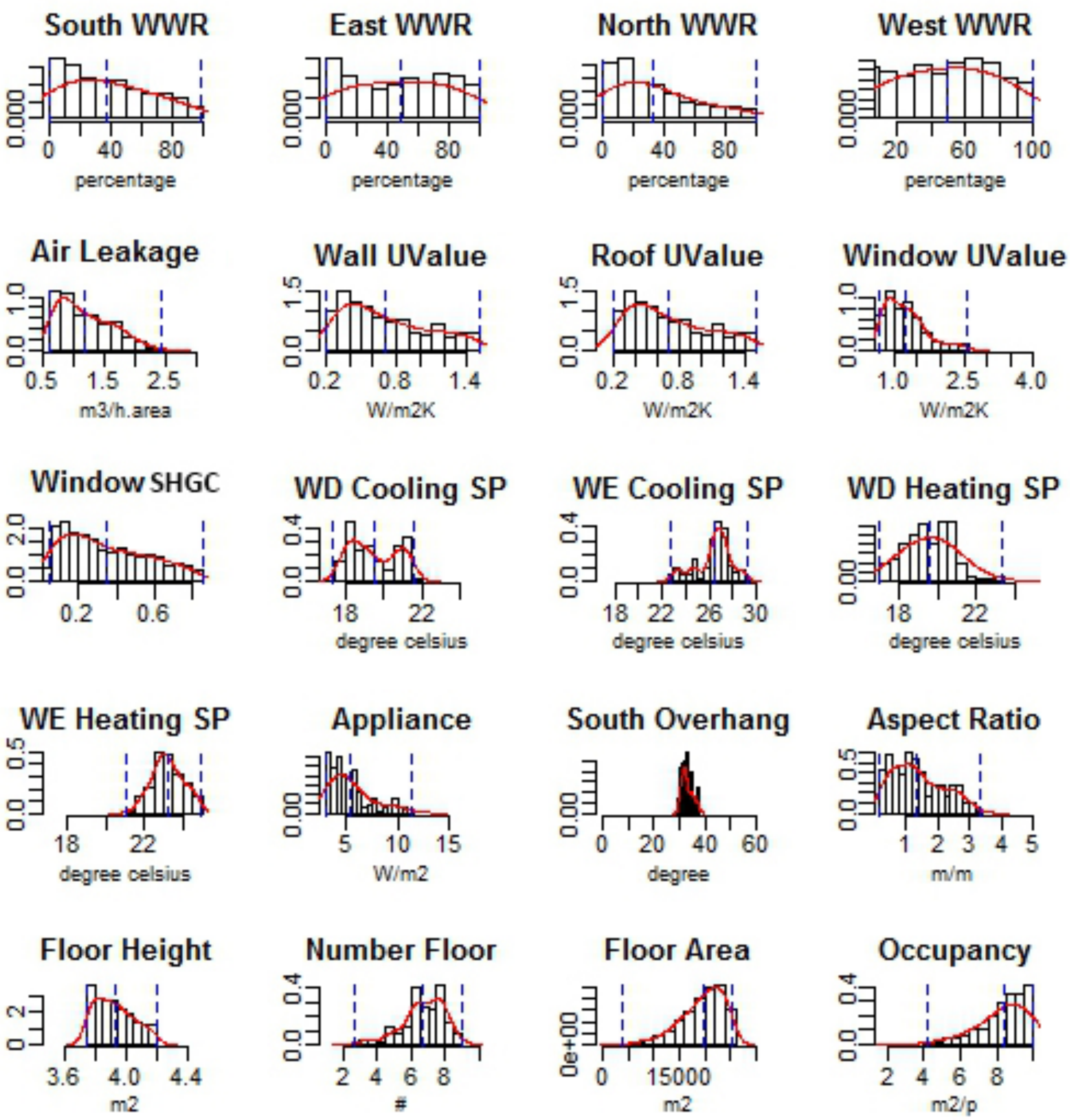


Figure 5.7(c) Chicago case study; design scenario Chicago _3

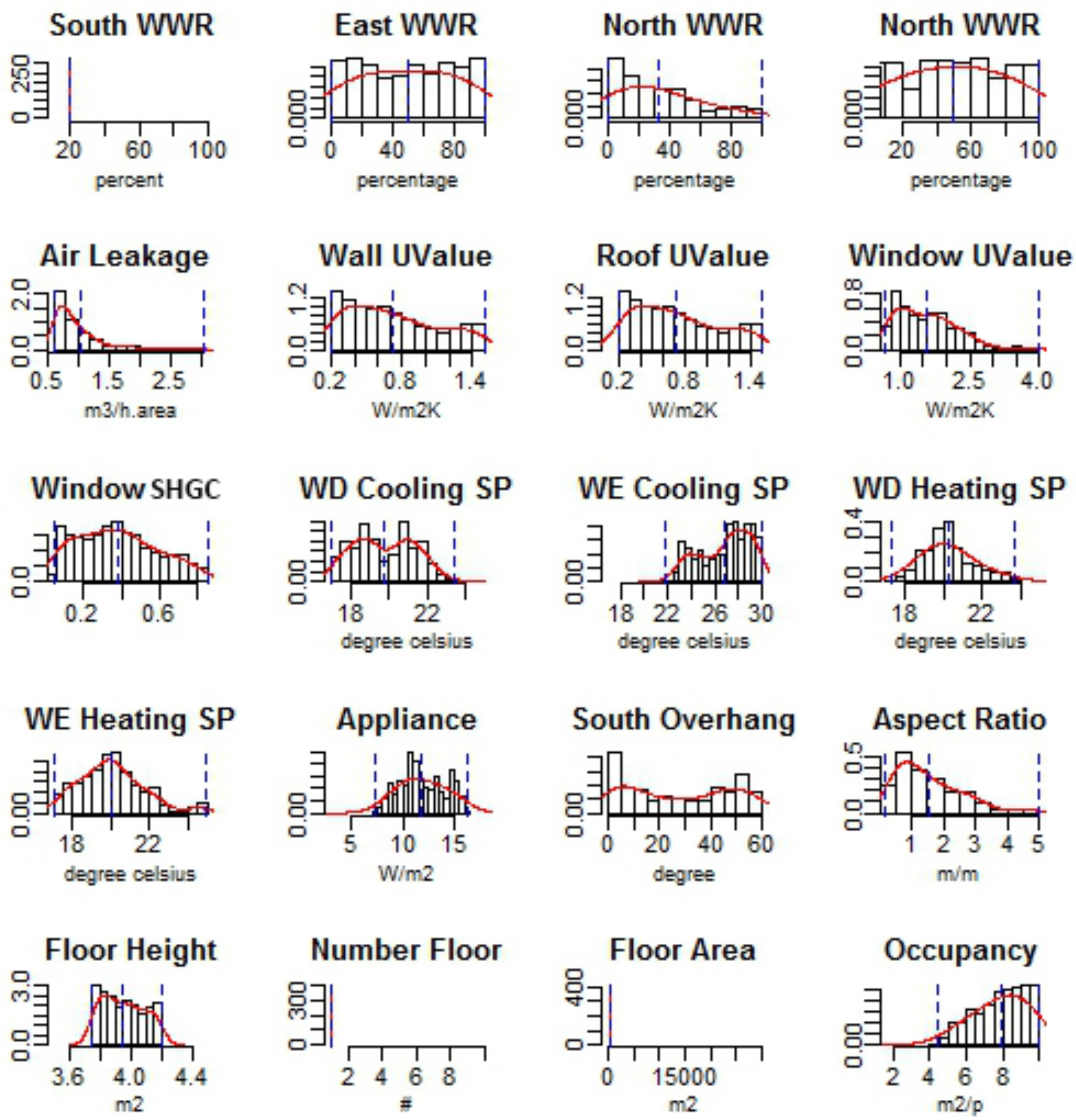


Figure 5.7(d) Chicago case study; design scenario Chicago _3_1

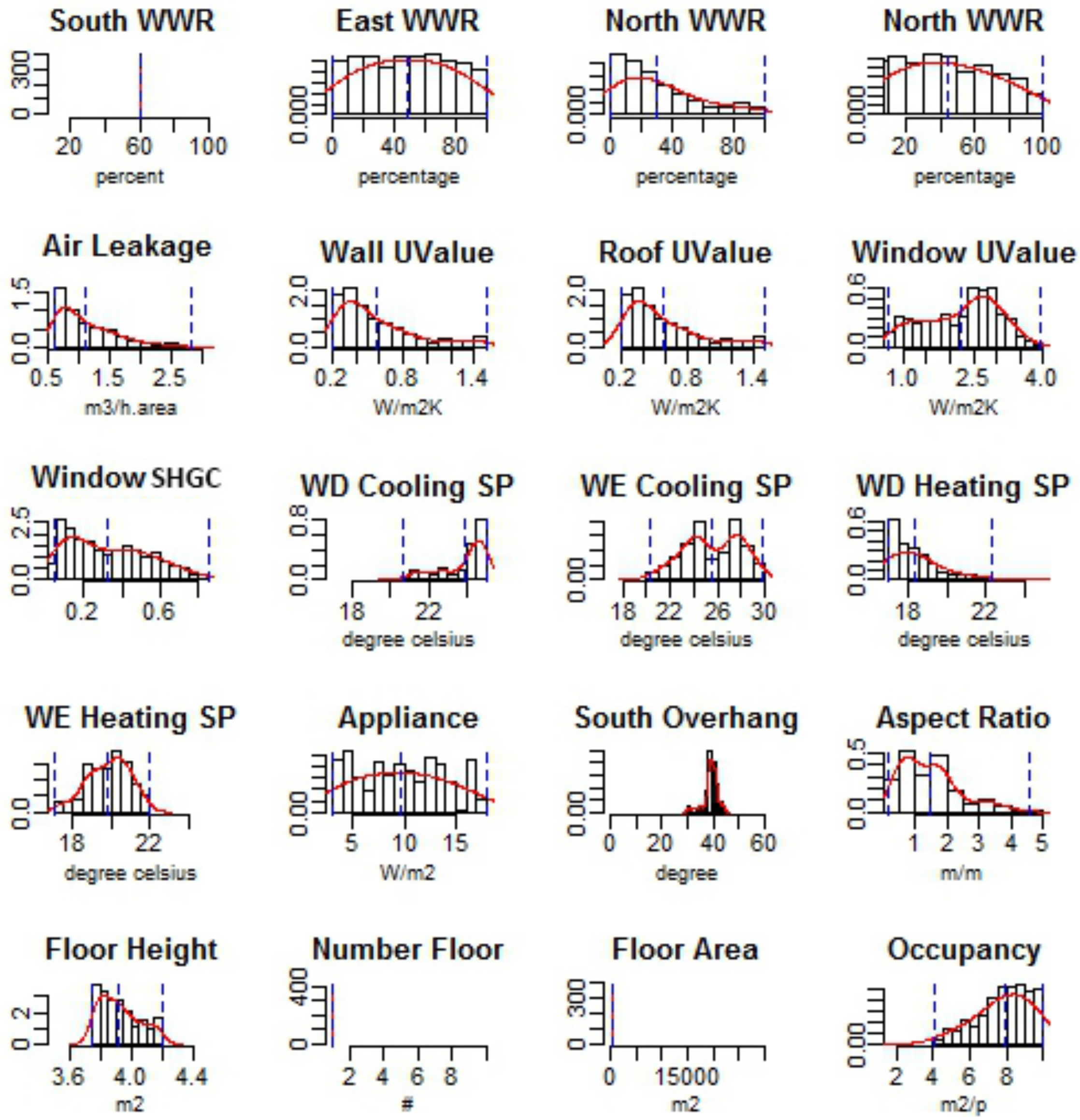


Figure 5.7(e) Chicago case study; design scenario Chicago _3_2

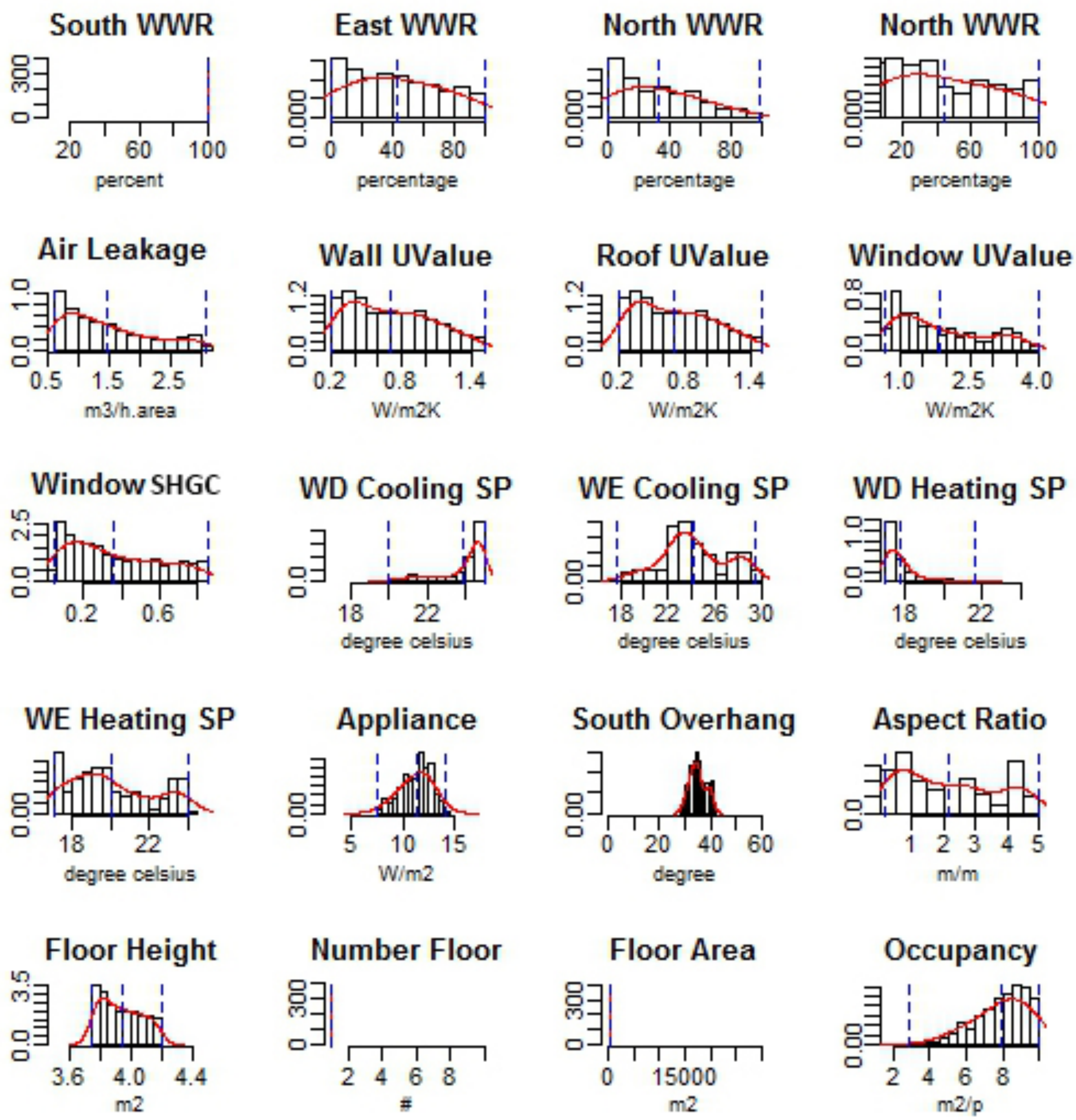


Figure 5.7(f) Chicago case study; design scenario Chicago _3_3

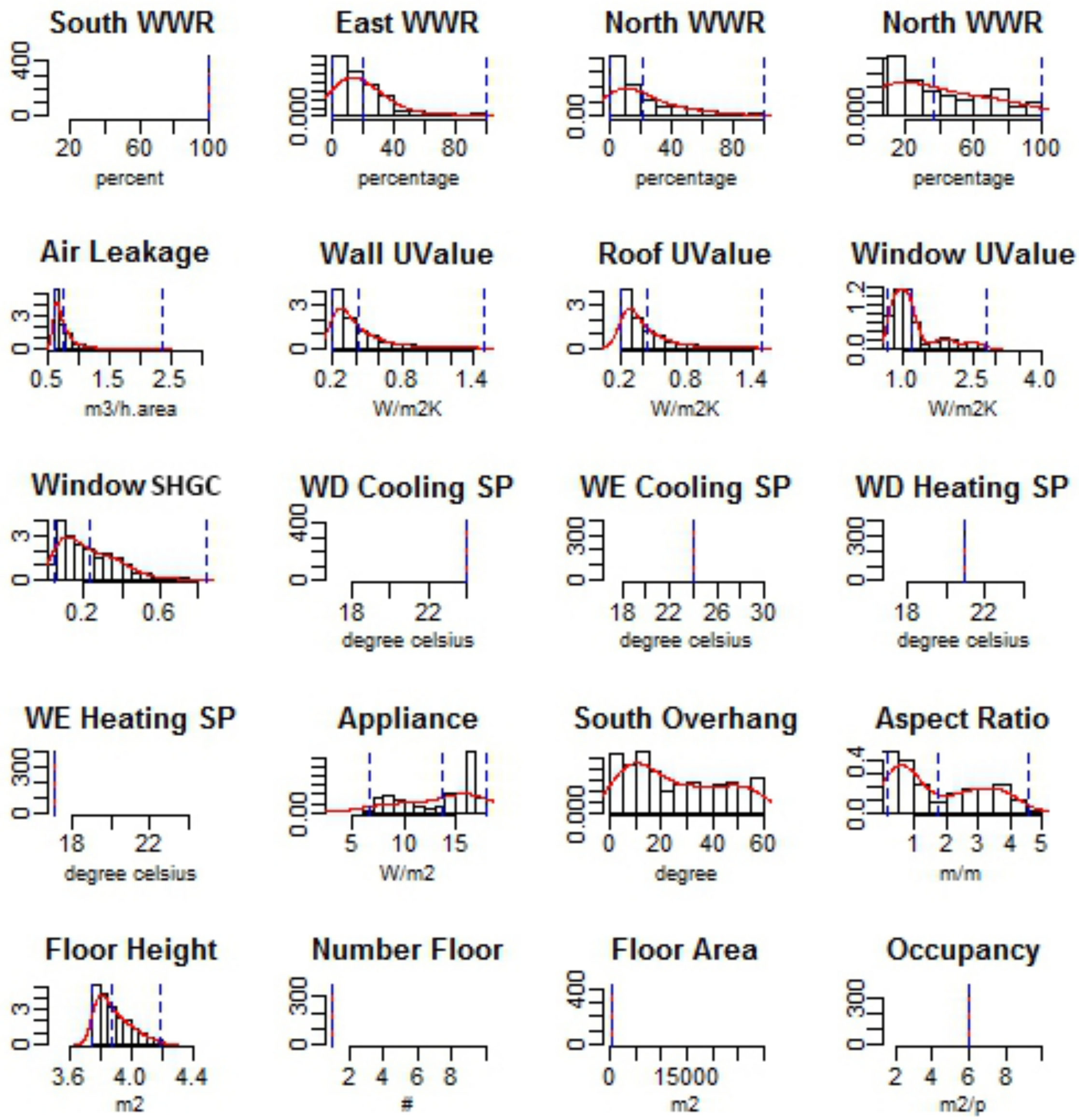


Figure 5.7(g) Chicago case study; design scenario Chicago_3_3_1

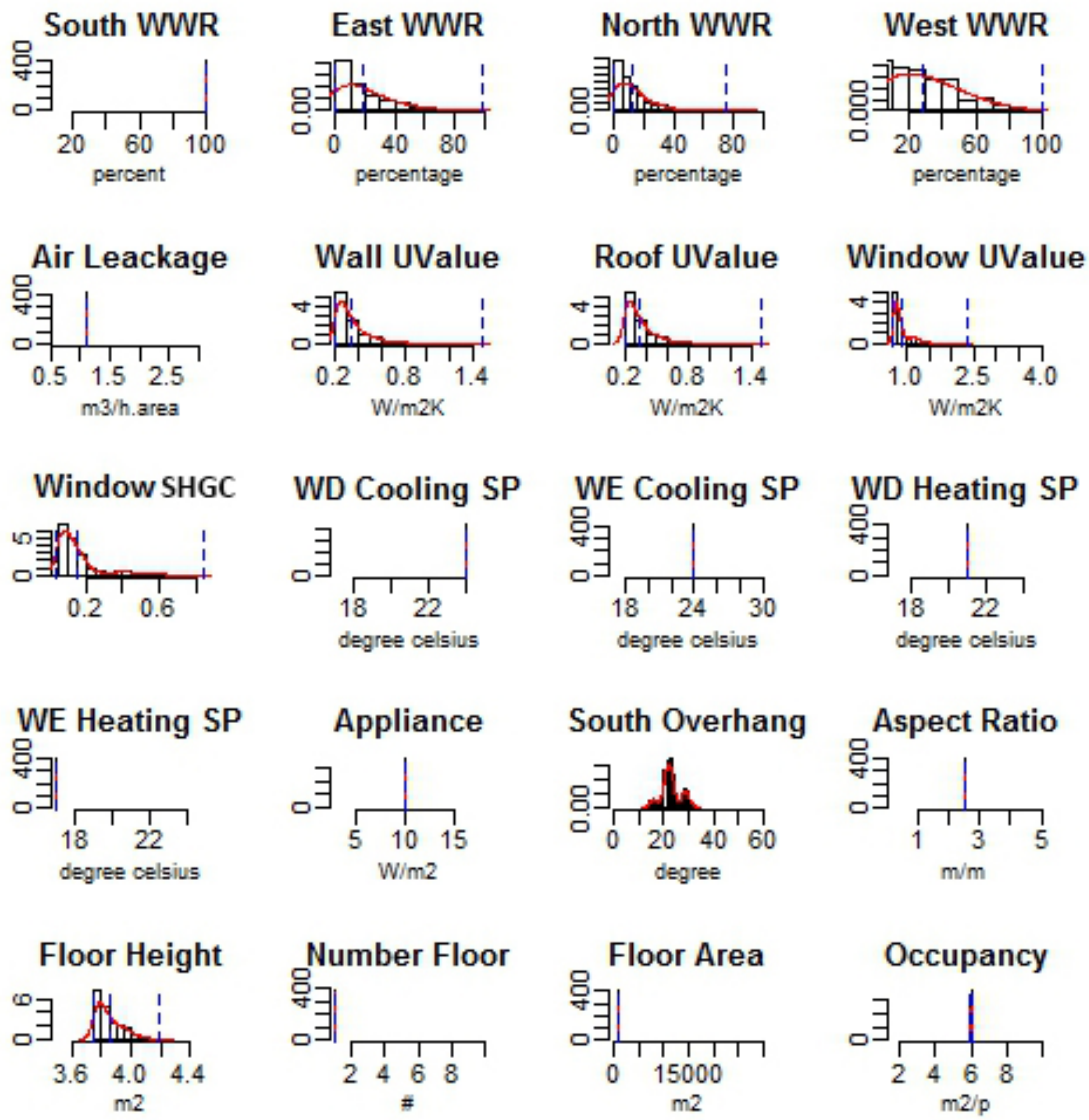


Figure 5.7(h) Chicago case study; design scenario Chicago_3_3_2

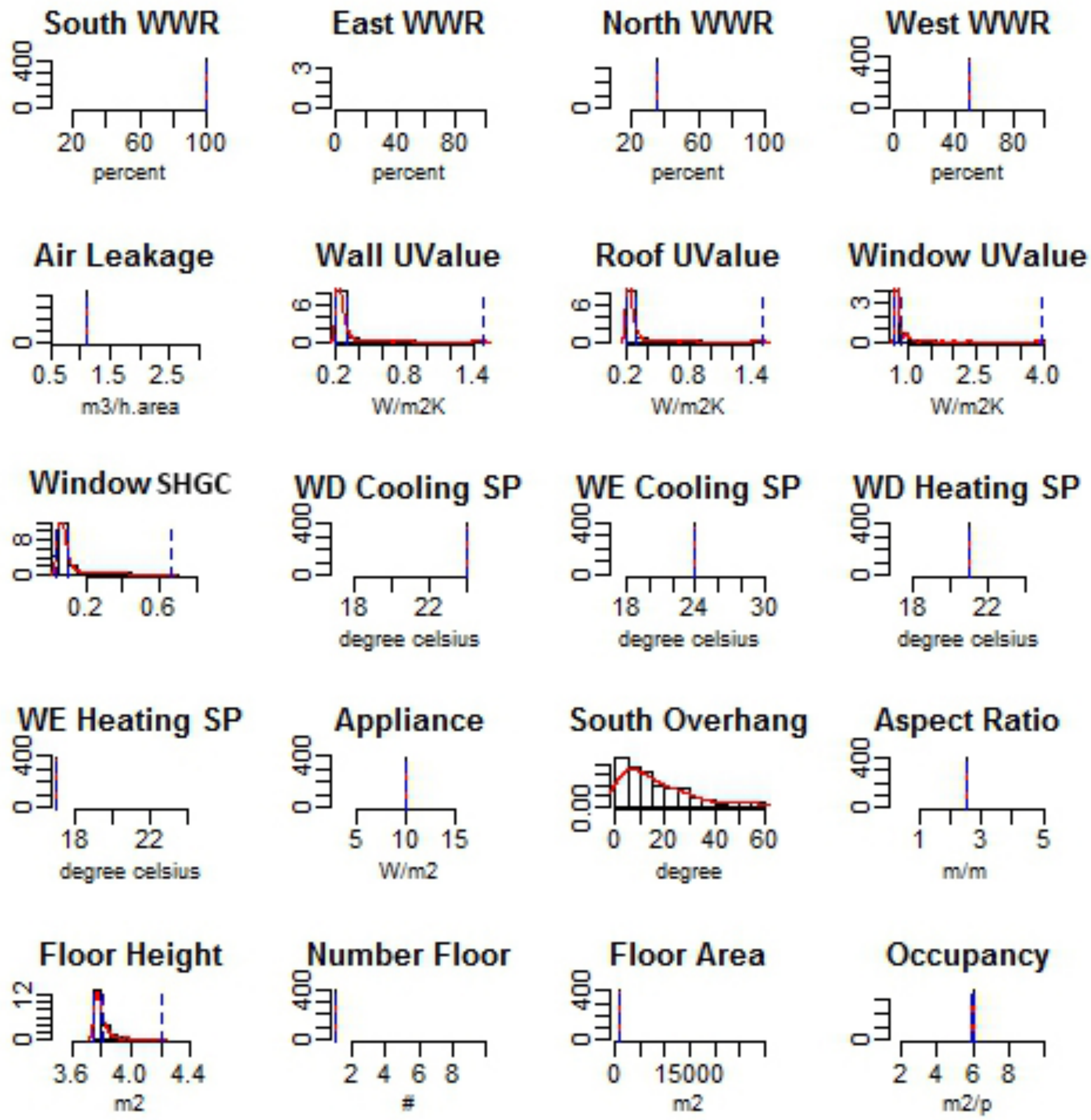


Figure 5.7(i) Chicago case study; design scenario Chicago_3_3_3

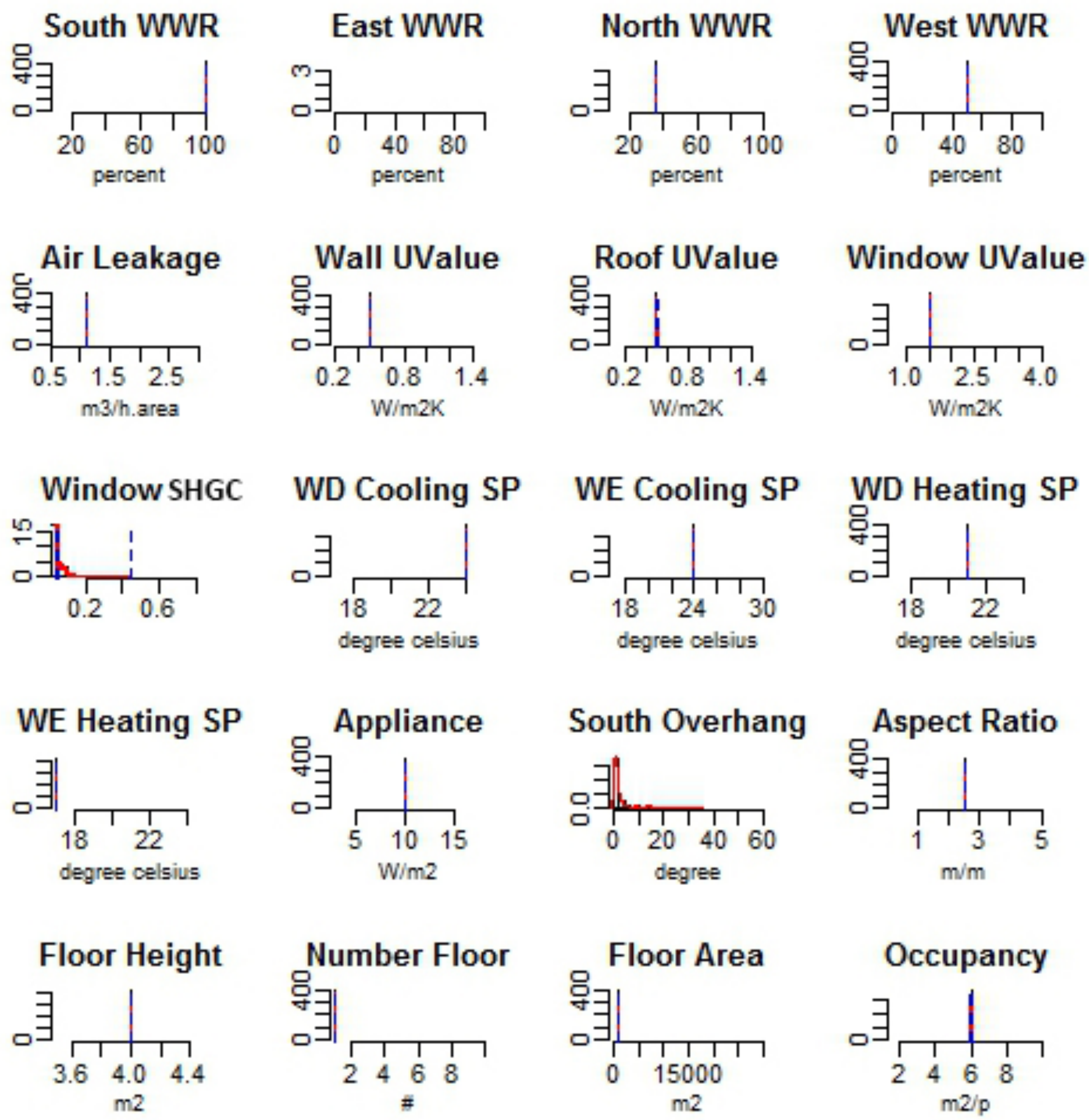


Figure 5.7(j) Chicago case study; design scenario Chicago_3_3_4

5.2. DESIGN OF ELEMENTARY SCHOOL IN LOS ANGELES

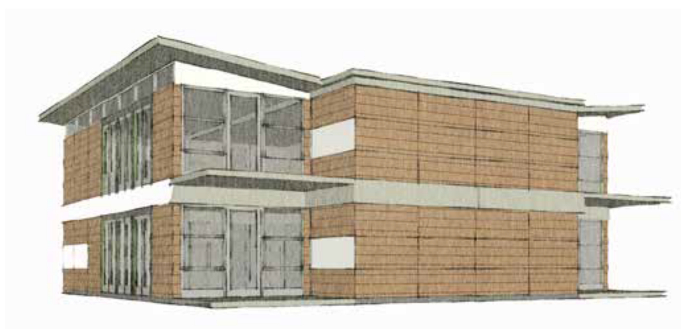


Figure 5.8 Modular school building in Los Angeles; designed by Perkins+Will

A modular classroom similar to the previous case study is going to be designed for a site in Los Angeles, CA, but in two stories. Having an aggressive energy performance objective, the designer is going to design a two-story structure with a floor area of 250 square meters. Figure 5.9 and table 5.5 show the histogram and values of the elementary schools thermal load in Los Angeles, and table 5.6 lists all design scenarios considered for this case study. The school project requires providing a lot of view and daylight through the south and north façades and to have at least 70% WWR for these two facades. Knowing the floor area, numbers of floors, north and south WWR, as well as cooling and heating setpoints, designers are going to make a decision about the buildings' aspect ratio. Three options of one, two and three aspect ratios are proposed by the team to investigate how each option affects the rest of the parameters (design scenarios LA_3-1, LA_3-2 and LA_3-3).

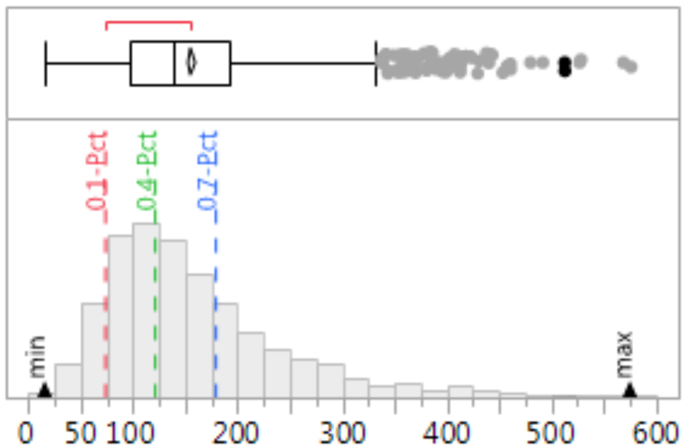


Figure 5.9 Histogram of thermal performance space for school buildings in Los Angeles

Table 5.5 Thermal performance possibilities for school buildings in Los Angeles

Case Study	***Min***	***10 percentile***	***40 percentile***	***70 percentile***	***Max***
CS2-LA	14.37	72.28	120.35	177.92	576.57

Table 5.6 design scenarios for Los Angeles elementary school case study

STEP I		STEP II			STEP III	
Scenario	**Objective**	**Scenario**	**Constraints**	**Alternatives**	**Scenario**	**Iterative process of making decision**
LA_1	Thermal load<=177.92					
LA_2	Thermal load<=120.35					
LA_3	Thermal load<=72.28					
		LA_3-1	Setpoints=21, Floor area=250, #floor=2, NWWR=SWWR=0.7	AR=1		
		LA_3-2	Setpoints=21, Floor area=250, #floor=2, NWWR=SWWR=0.7	AR=2		
		LA_3-3	Setpoints=21, Floor area=250, #floor=2, NWWR=SWWR=0.7	AR=3		
					LA_3-1-1	Occupancy=8, Appliance=10, Lighting=10
					LA_3-1-2	EWWR=0.7, WWWR=0.25
					LA_3-1-3	Window-UValue=3.8, SHGC=0.1
					LA_3-1-4	Air Leakage=2.1

The results of the comparison of three options are presented in figures 5.10 (d) to (f). These options show no difference at this stage of design, when there are still many undecided parameters available. After choosing the aspect ratio of one (AR=1) because of a functional requirement of the project and by estimating the occupancy, lighting and equipment loads in similar projects, the designers are going to make decisions about the east and west fenestration in scenario LA_3-1-2. The distributions of east and west windows to wall ratio in figure 5.10(g) provides freedom in their design. That causes the design team to choose these variables based on other requirements rather than energy, including view, daylight and aesthetic objectives. Consequently designers will choose windows to wall ratio of 70% and 25% for east and west façade respectively (scenario LA_3-1-3).

The interesting point at this case study is that the material conductivity of wall and roof are not among the most significant parameters, and windows U-Value has a relatively small impact, which is different from what is usually assumed. The scenario of this case study suggests having higher window U-Values, which might be the result of having high internal heat gain for this climate, where high conductivity of glass might help in transferring heat between inside and outside. However windows solar heat gain coefficient (SHGC) is one of the most important parameters, which should be reduced to prevent heat through radiation. That's why designers will choose such a glazing with lower SHGC and preferably higher U-Value, which is also more cost effective one (scenario LA_3-1-3 shown in figure 5.10(i)). And finally the very last decision is associated with the only remaining parameter, which is the building air leakage, and the inverse approach suggests this variable to be between 1.4 and 3, with a mean value of 2.2 (figure 5.10(j)).

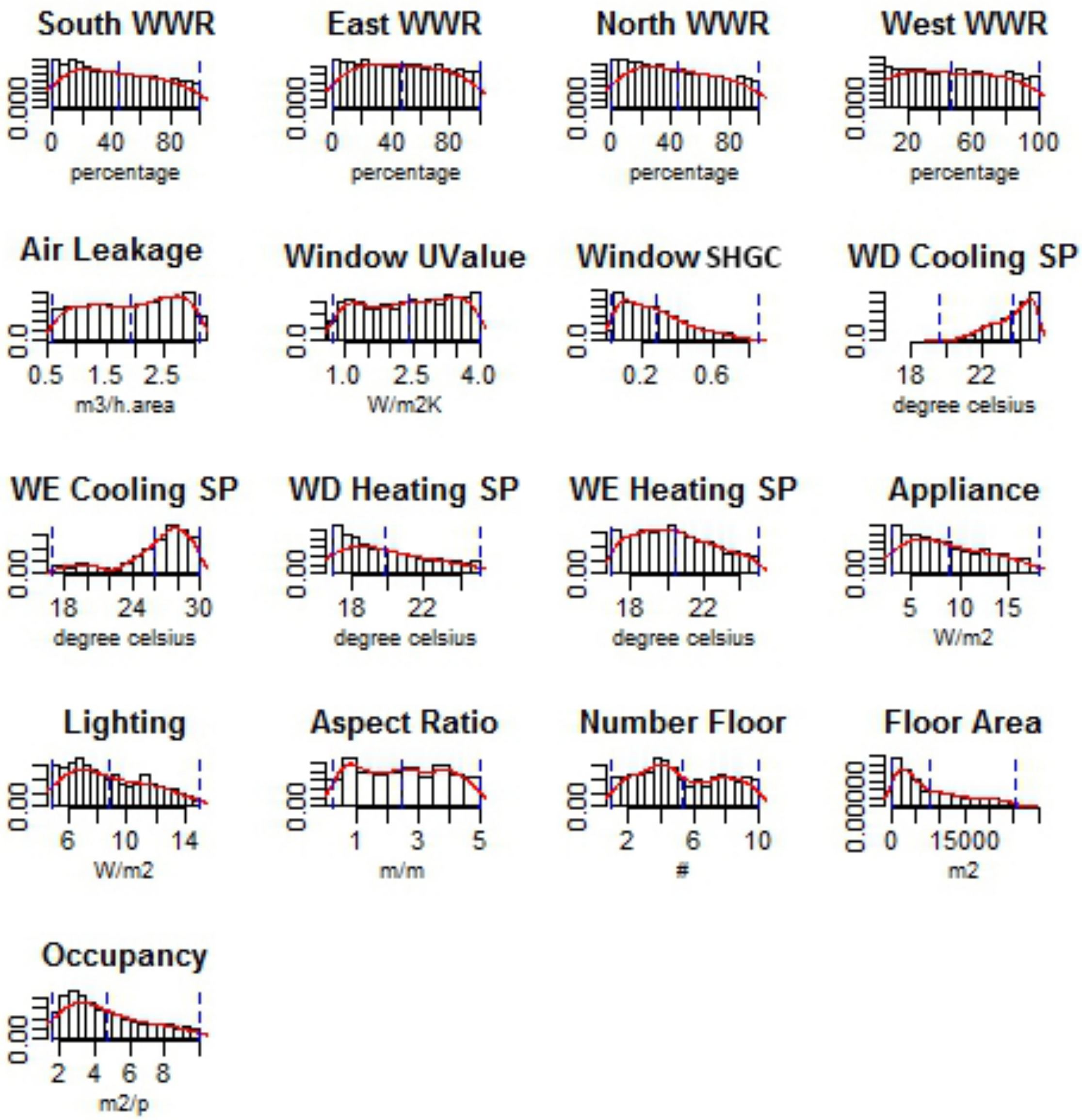


Figure 5.10(a) Los Angeles case study; design scenario LA _1

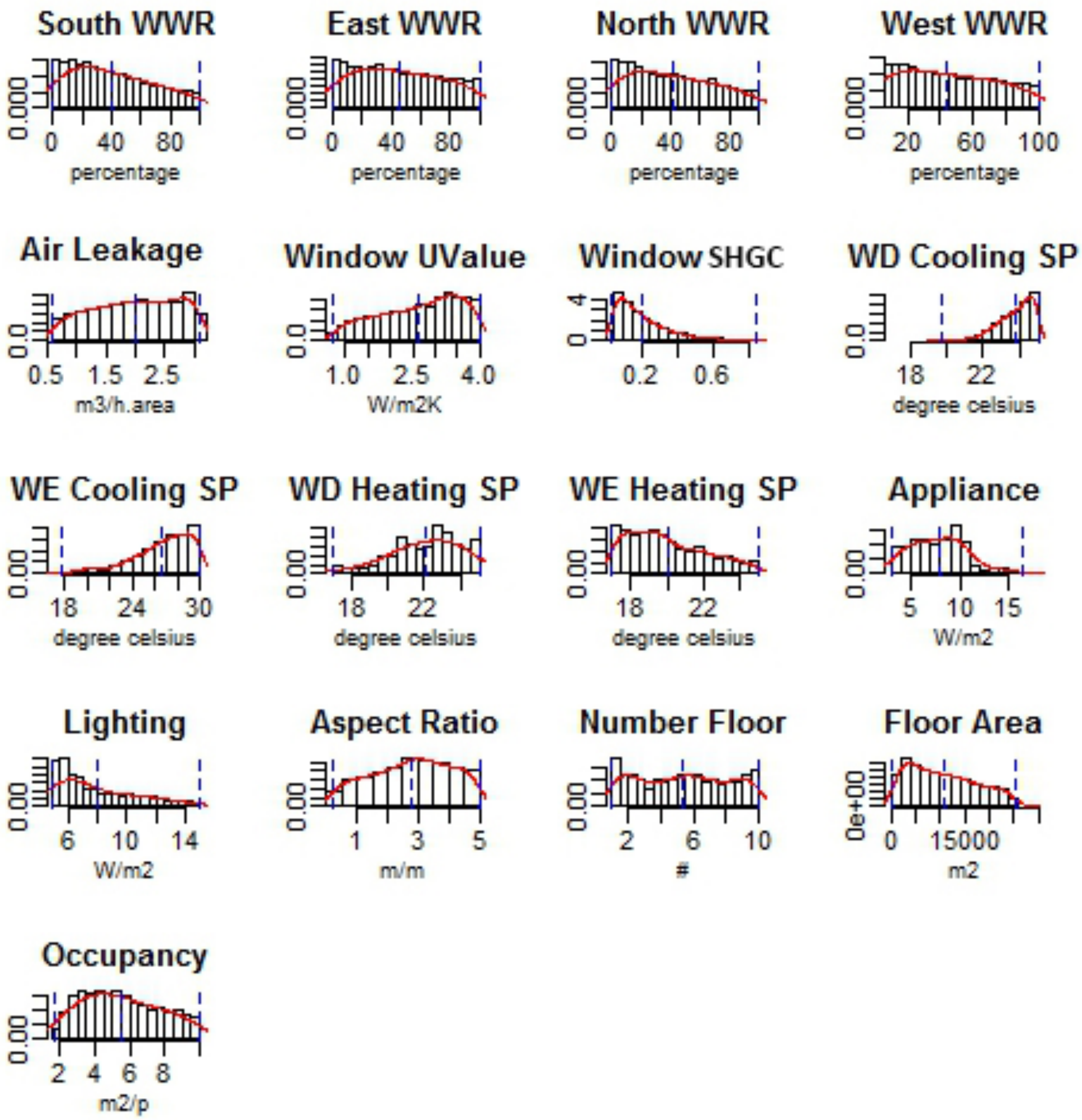


Figure 5. 10(b) Los Angeles case study; design scenario LA _2

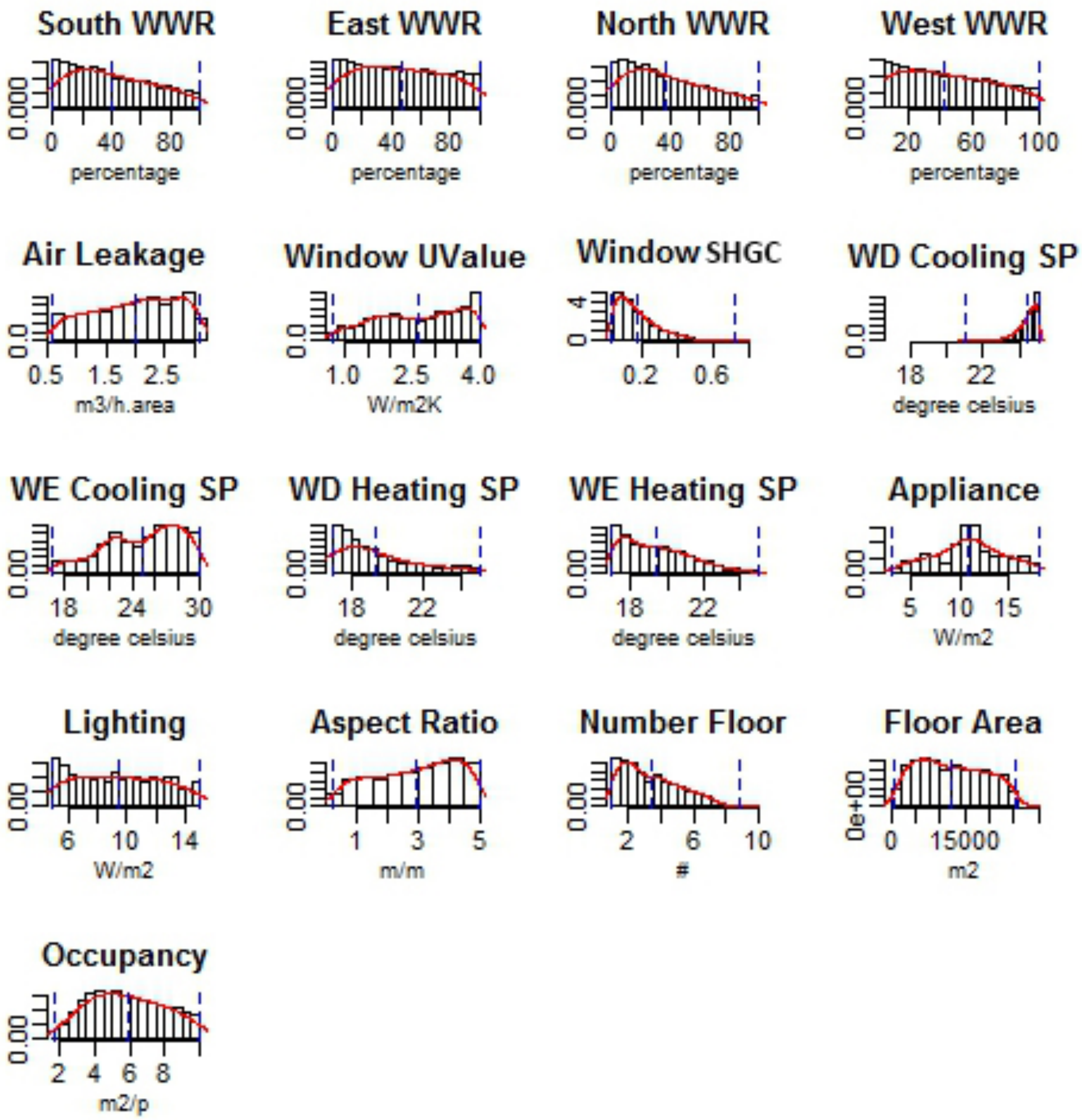


Figure 5. 10(c) Los Angeles case study; design scenario LA _3

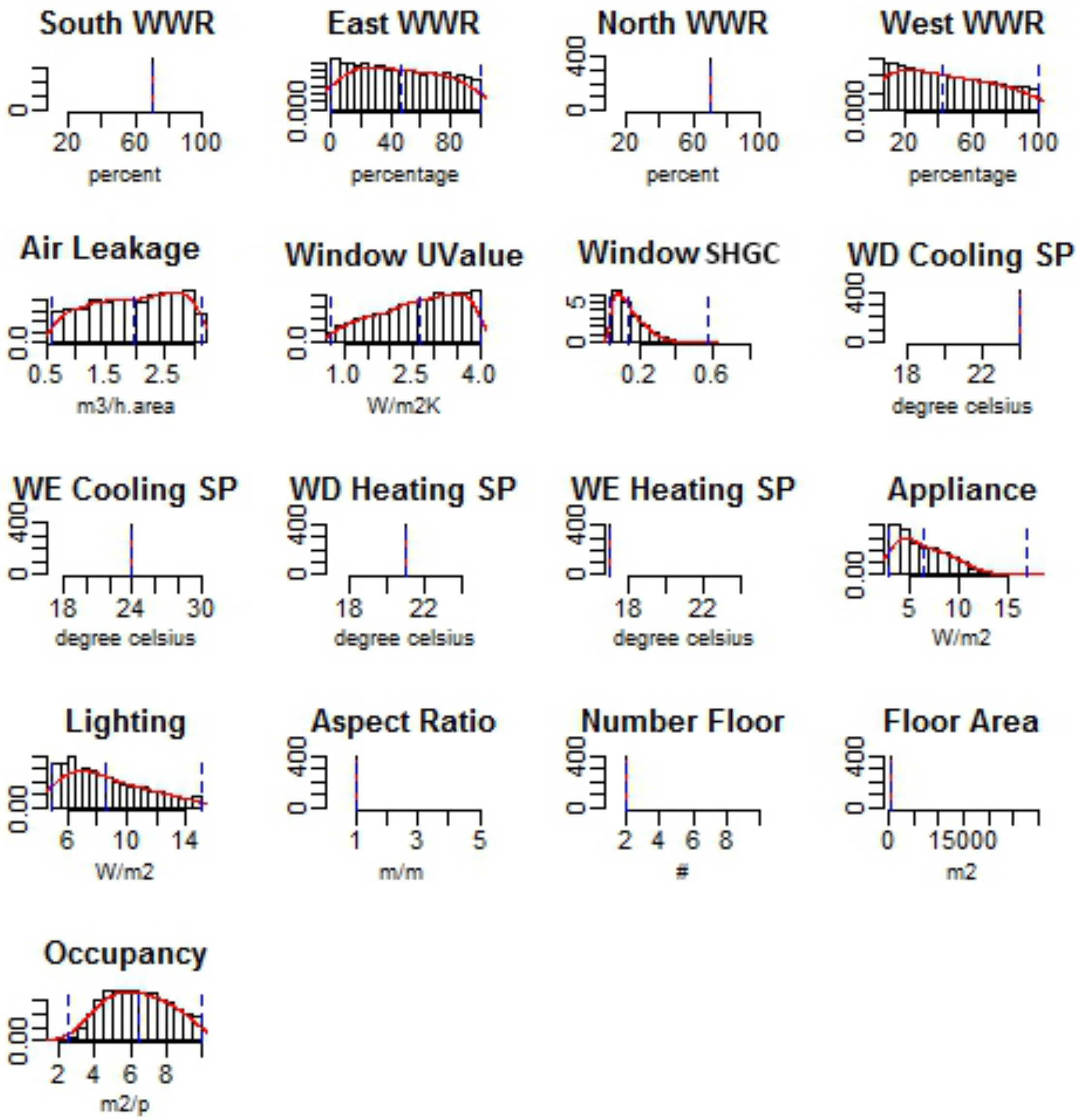


Figure 5. 10(d) Los Angeles case study; design scenario LA _3-1

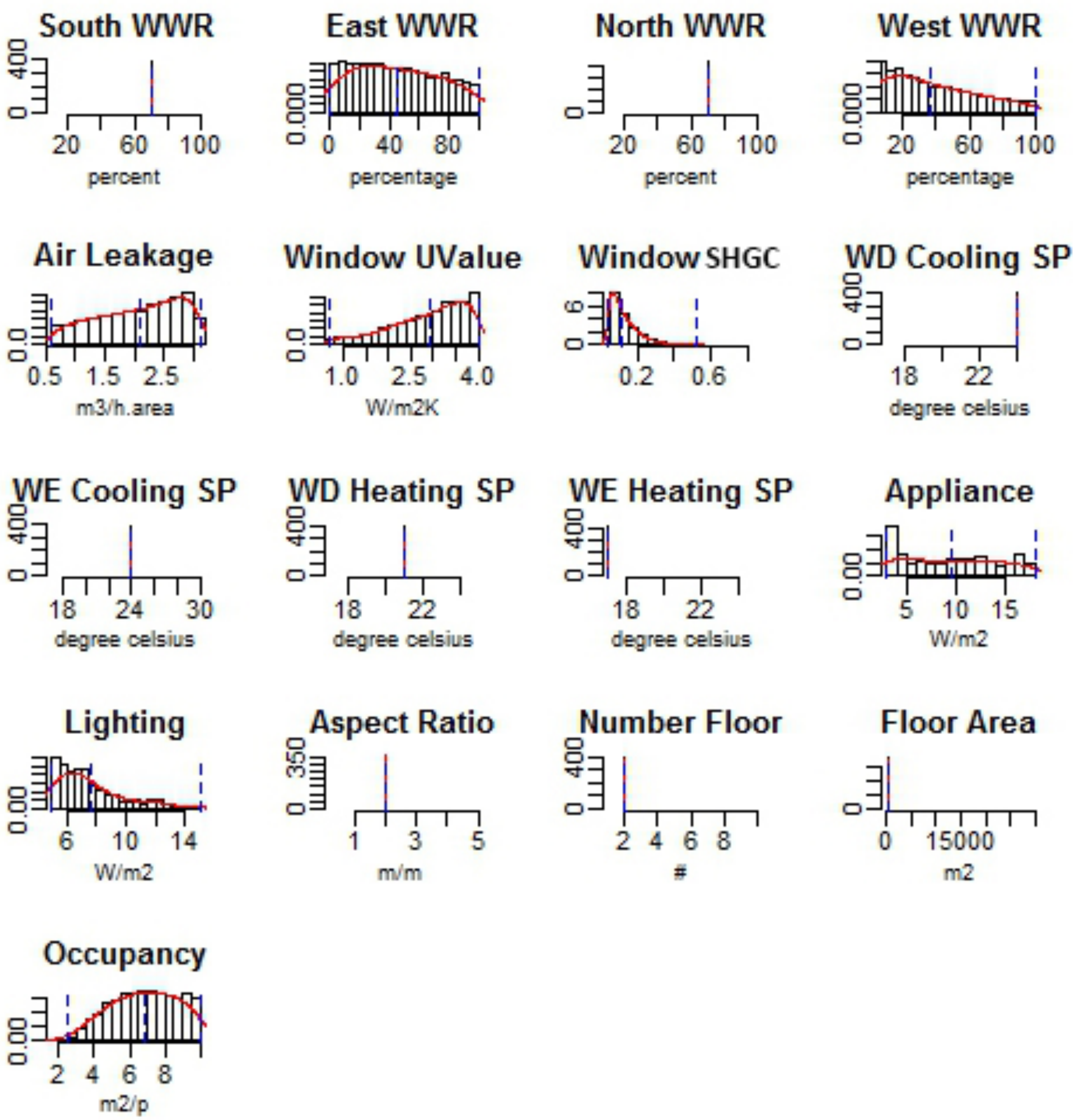


Figure 5.10(e) Los Angeles case study; design scenario LA _3-2

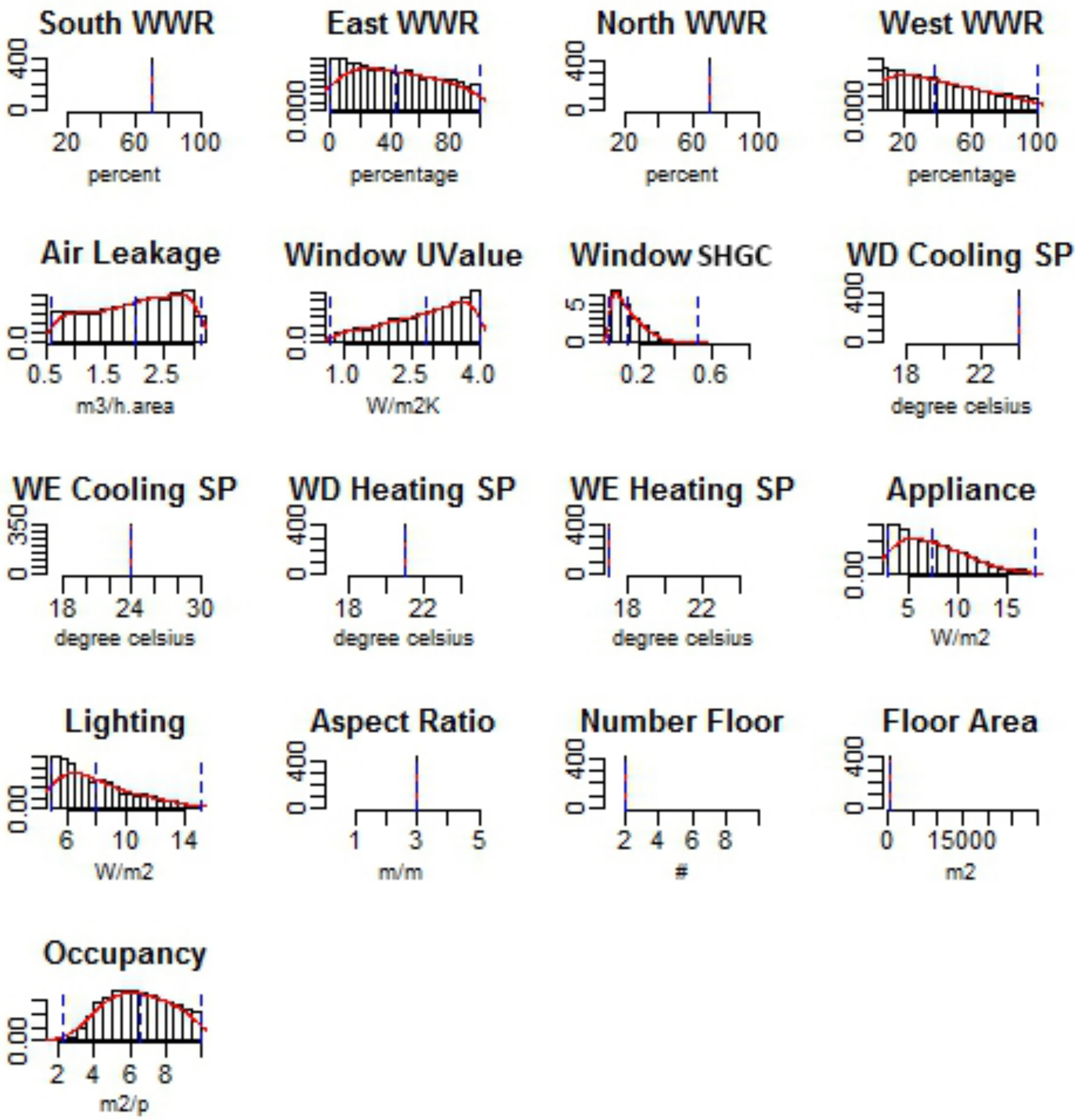


Figure 5.10(f) Los Angeles case study; design scenario LA _3-3

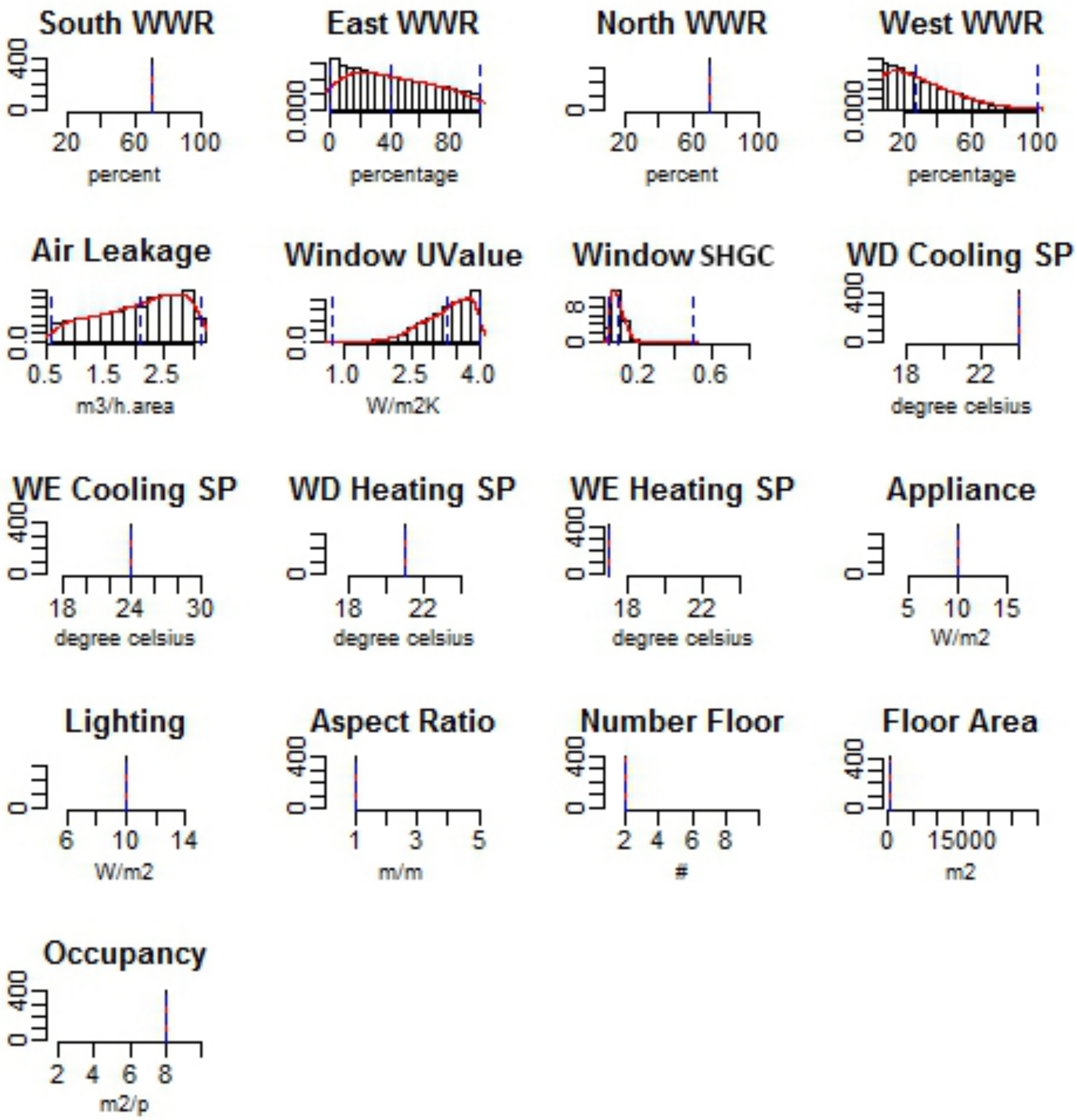


Figure 5.10(g) Los Angeles case study; design scenario LA _3-1-1

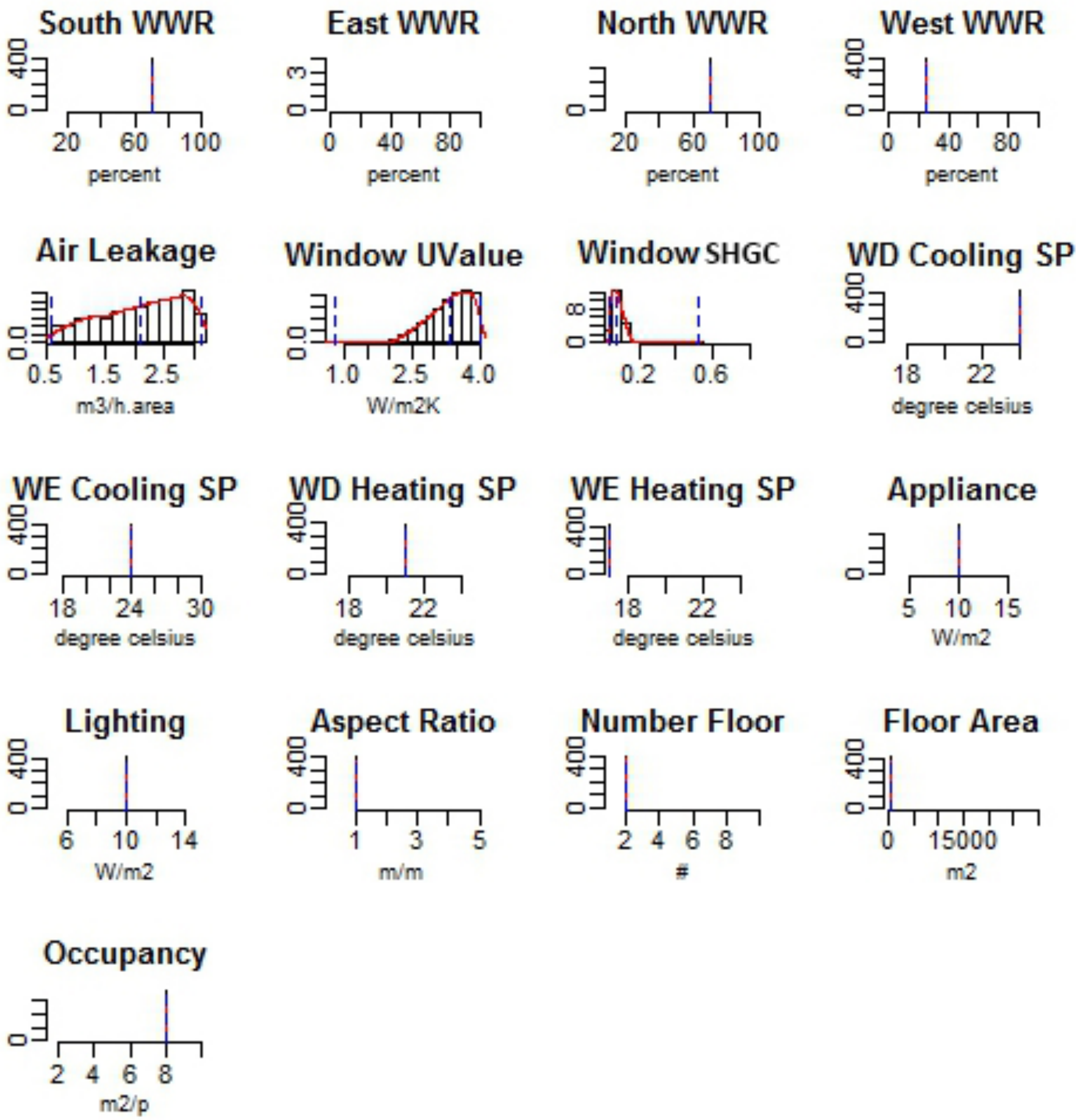


Figure 5.10(h) Los Angeles case study; design scenario LA _3-1-2

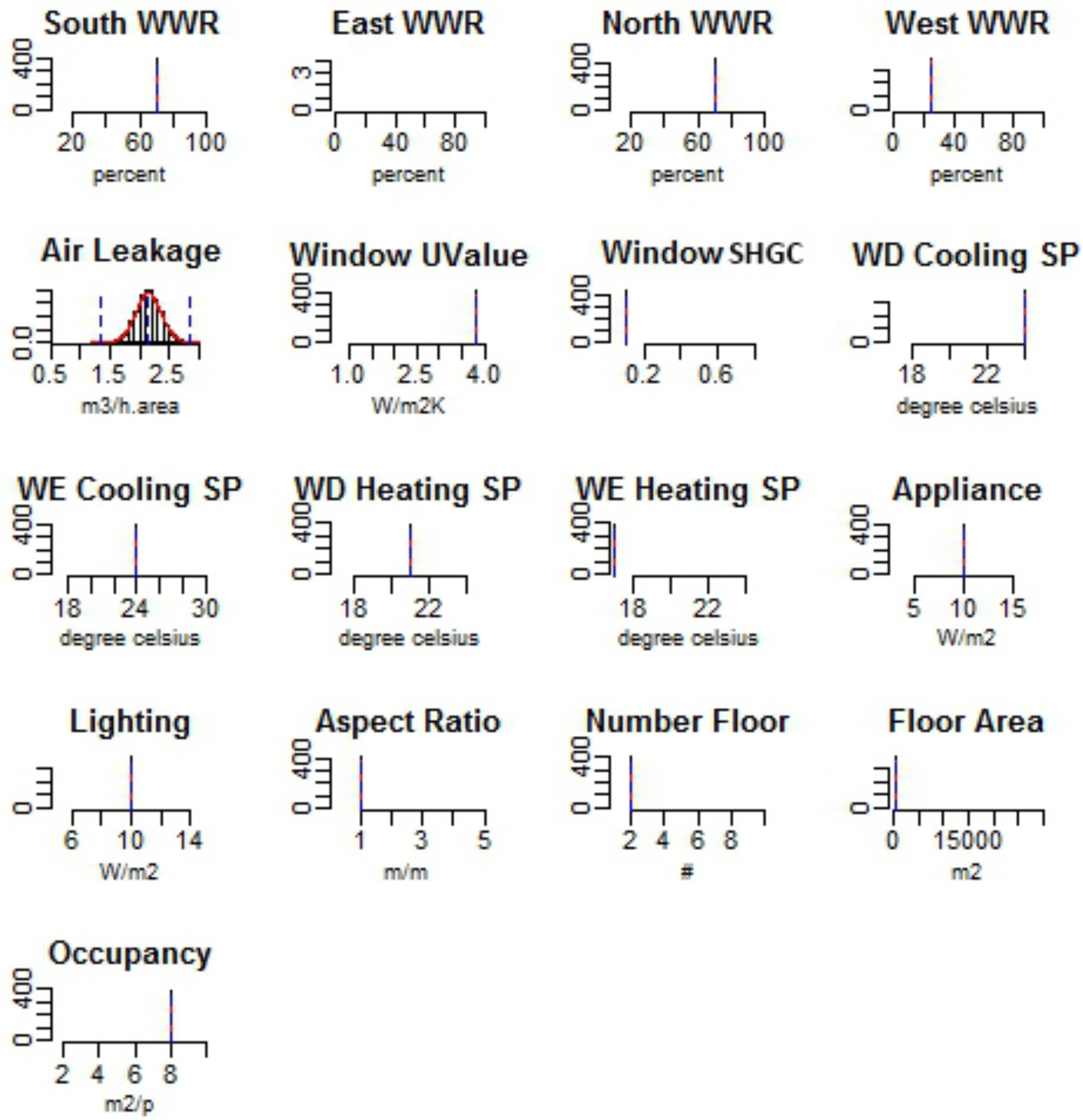


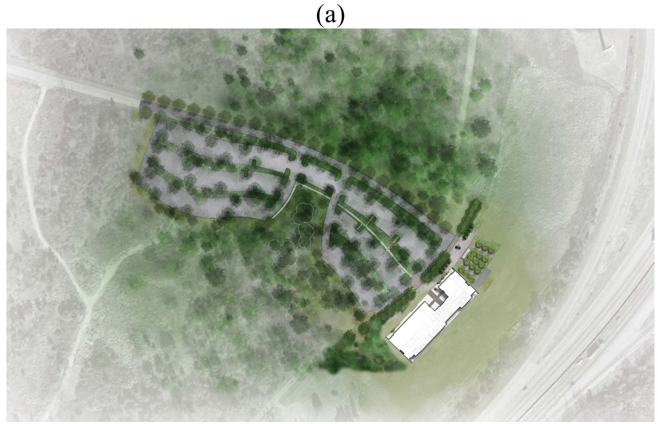
Figure 5.10(i) Los Angeles case study; design scenario LA _3-1-3

5.3. DESIGN OF MID-SIZE OFFICE IN ATLANTA

Figure 5.11 medium-size office building in Atlanta; designed by Perkins+Will

The third case study is the design of a medium-size office building for BMW in Atlanta. The design requires a three-story office building with the gross floor area of 8500 square meters. Due to the very restricted functional requirements by the client, the massing and configuration of the building is fixed, and designers explore different orientations as the first step. The three alternatives proposed are having the orientation of 0, 45, and 90 degree in the site, as shown in picture 5.11, and summarized in table 5.8. The histogram of the thermal load for mid-size office buildings in Atlanta is also displayed in figure 5.13.

(a)



(b)

(c)

Figure 5.12 Three building orientation options to compare for BMW office in Atlanta

At this stage of design, comparing alternatives corresponds to performing feasibility analysis. Unless the inverse approach gives no result, which means that there is no solution available for the scenario, due to interdependencies of parameters and high level of undecided parameter uncertainty, designers can hardly make a decision with confidence. As you can find in figures 5.14(d) to (f), there is hardly any obvious distinction between these options, and designers choose the second alternative because of the better accessibility of the site. After they estimate the number of occupant, and confirm the size and configuration of southeast façade so that the building be visible and attractive from the main highway, designers gradually make decision about the other facades as well as the materials, and run the inverse analysis each time to confirm they are bounded to their energy objective. (Design scenarios of Atlanta_3-2-1 to Atlanta_3-2-3 shown in figures 5.14(g) to (i)).

Based on the values decided for opaque and glazing thermal properties, the final stage leaves the designers no choice except choosing an overhangs factor of 60 for both south and west windows, according to the histograms of figure 5.14(i), design scenario of Atlanta_3-2-3. Because the design team are not interested in adding any shading elements on south, they explore other thermal properties of glazing to prevent modifying their proposed façade appearance. After using the inverse modeling approach to explore the design space, a glazing U-Value of 0.7and SHGC of 0.04 give them the freedom to get rid of shading on the south and southeast, as listed as design scenario Atlanta_3-2-4 and represented in figure 5.14(j).

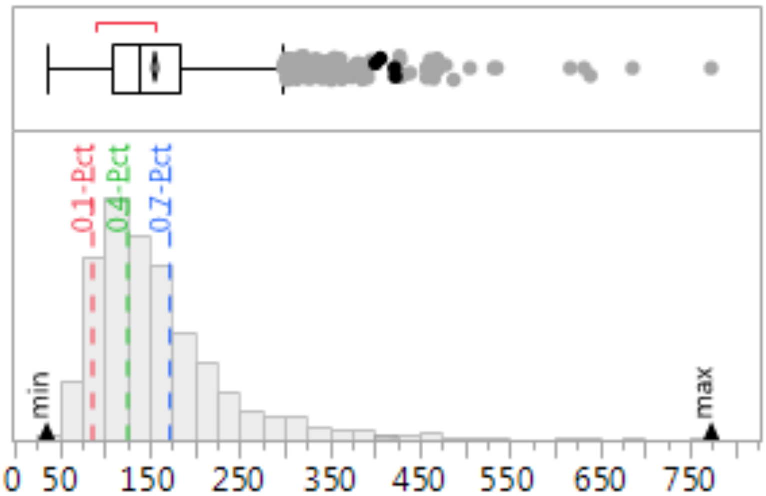


Figure 5.13 Histogram of thermal performance for office buildings in Atlanta

Table 5.7 Thermal performance possibilities for office buildings in Atlanta

Case Study	***Min***	***10 percentile***	***40 percentile***	***70 percentile***	***Max***
CS3-Atlanta	36.81	85.34	124.35	171.07	774.055

Table 5.8 Design scenarios for the case study of Atlanta office building

STEP I		**STEP II**			**STEP III**	
Scenario	**Objective**	**Scenario**	**Constraints**	**Alternatives**	**Scenario**	**Iterative process of making decision**
Atlanta_1	Thermal load<=171.07					
Atlanta_2	Thermal load<=124.35					
Atlanta_3	Thermal load<=85.34					
		Atlanta_3-1	Floor area=8500, #floor=3, Setpoints=(21, 16, 24, 28), Appliance=Lighting=10	AR=2, Orientation=1		
		Atlanta_3-2	Floor area=8500, #floor=3, Setpoints=(21, 16, 24, 28), Appliance=Lighting=10	AR=2, Orientation=0		
		Atlanta_3-3	Floor area=8500, #floor=3, Setpoints=(21, 16, 24, 28), Appliance=Lighting=10	AR=0.5, Orientation=1		
					Atlanta_3-2-1	Occupancy=20, Air leakage=1.1, SWWR=0.6
					Atlanta_3-2-2	NWWR=0.6, EWWR=WWWR=0.2, F_Height=4
					Atlanta_3-2-3	Wall-UVualue=0.7, Roof-UValue=0.2, Wall-Abs=0.5, Window-UValue=3.5
					Atlanta_3-2-4	South-Overhang=60, West-Overhang=60, Window-SHGC=0.1

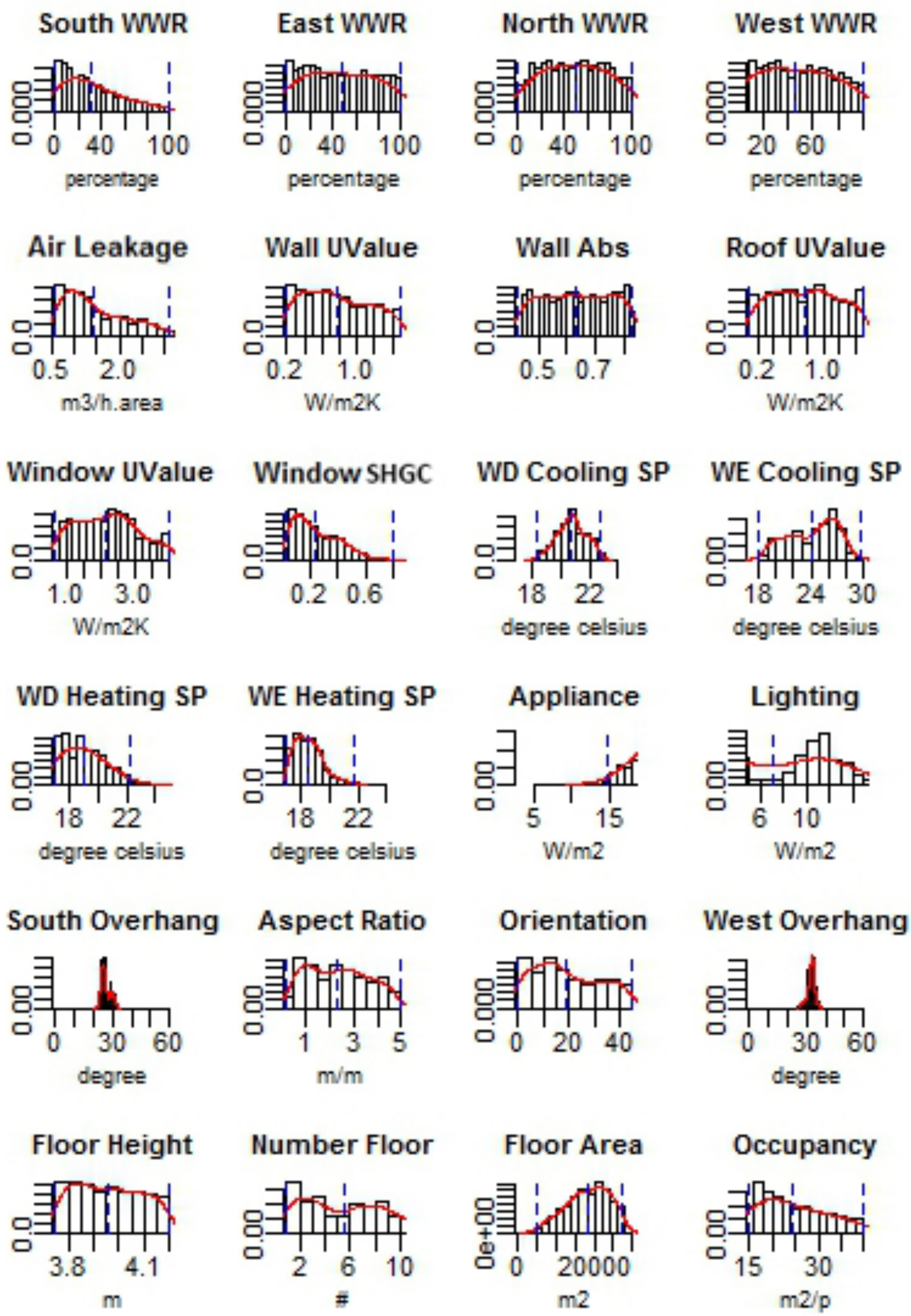


Figure 5.14(a) Atlanta case study; design scenario Atlanta _1

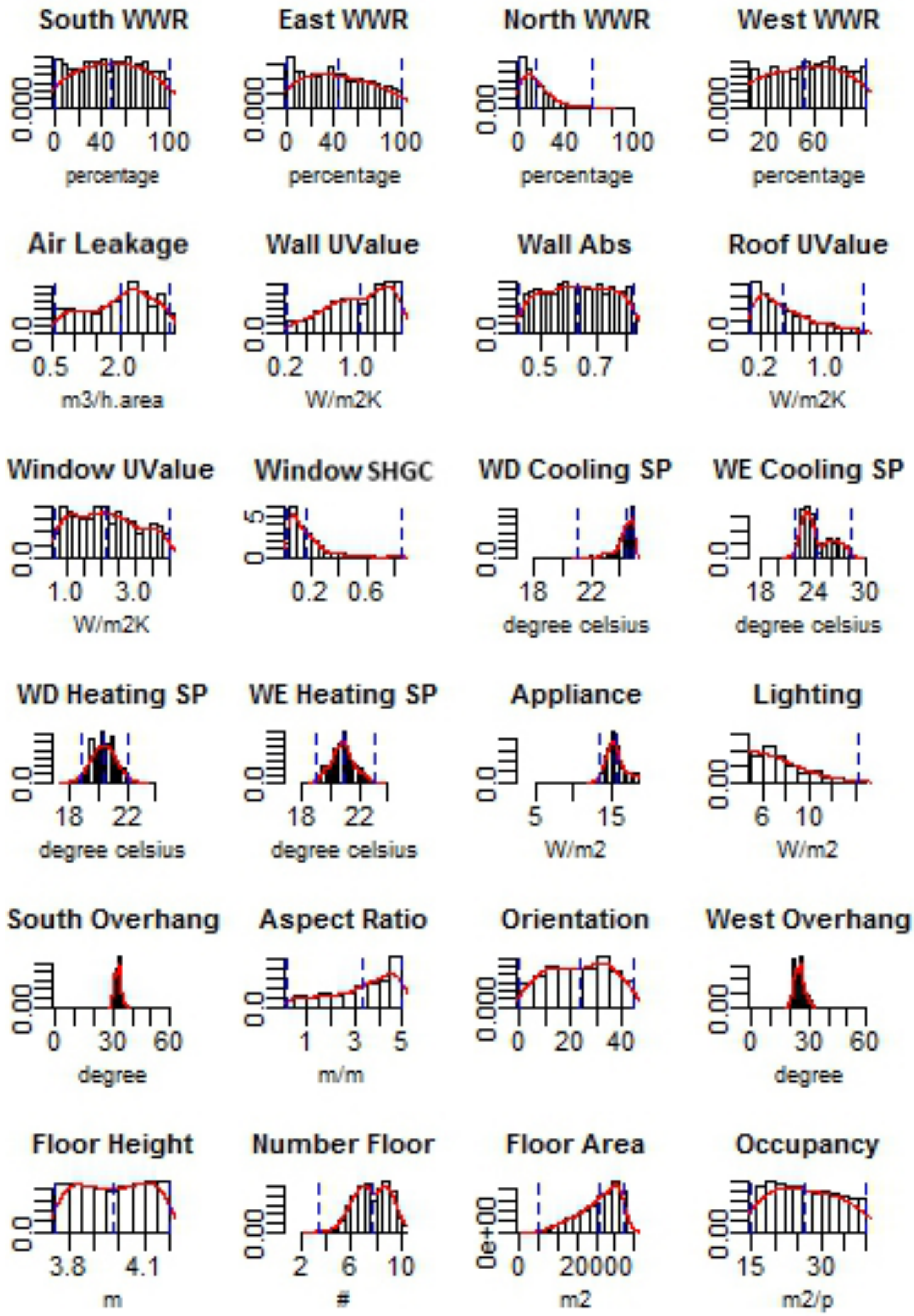


Figure 5.14(b) Atlanta case study; design scenario Atlanta _2

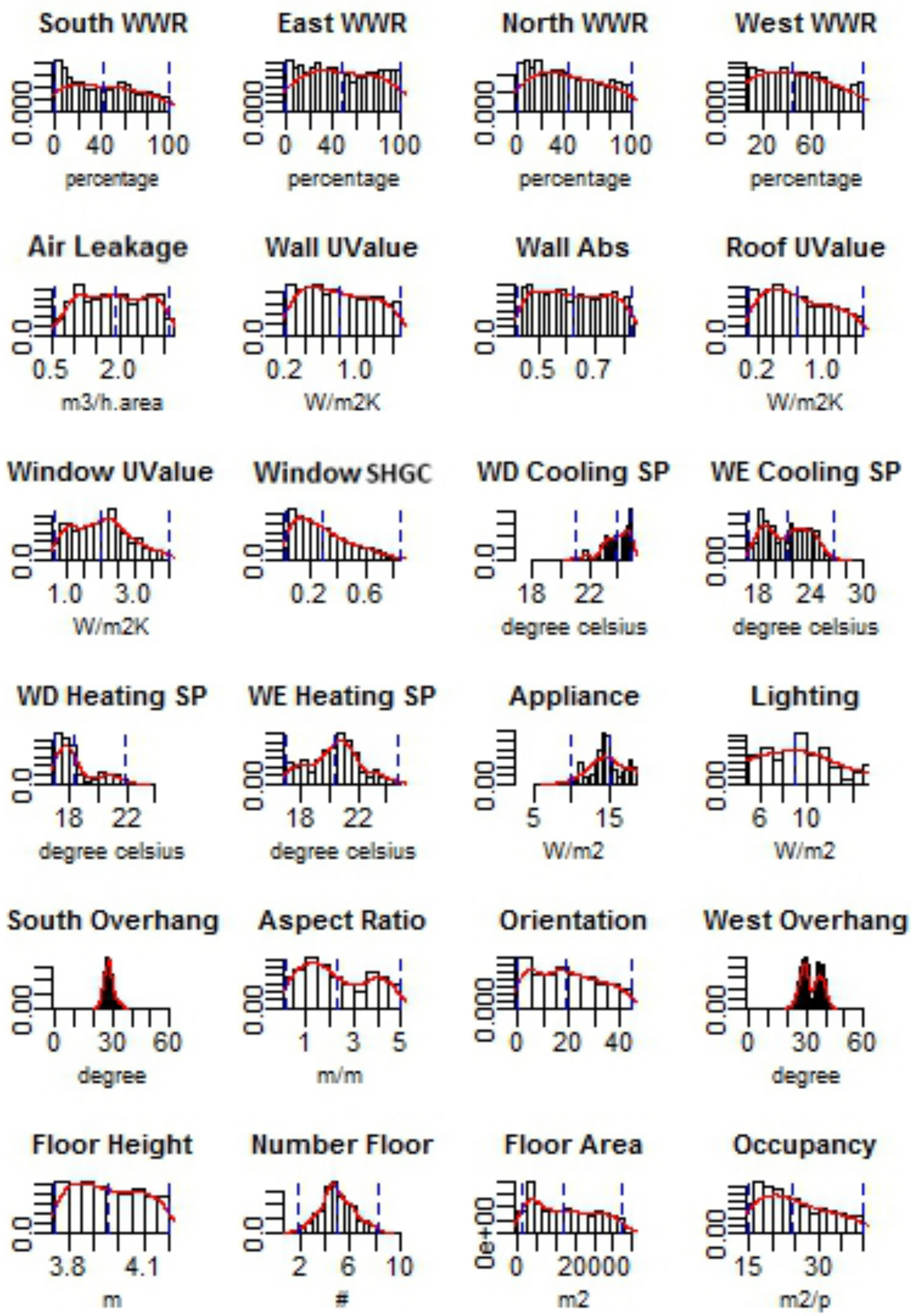


Figure 5.14(c) Atlanta case study; design scenario Atlanta _3

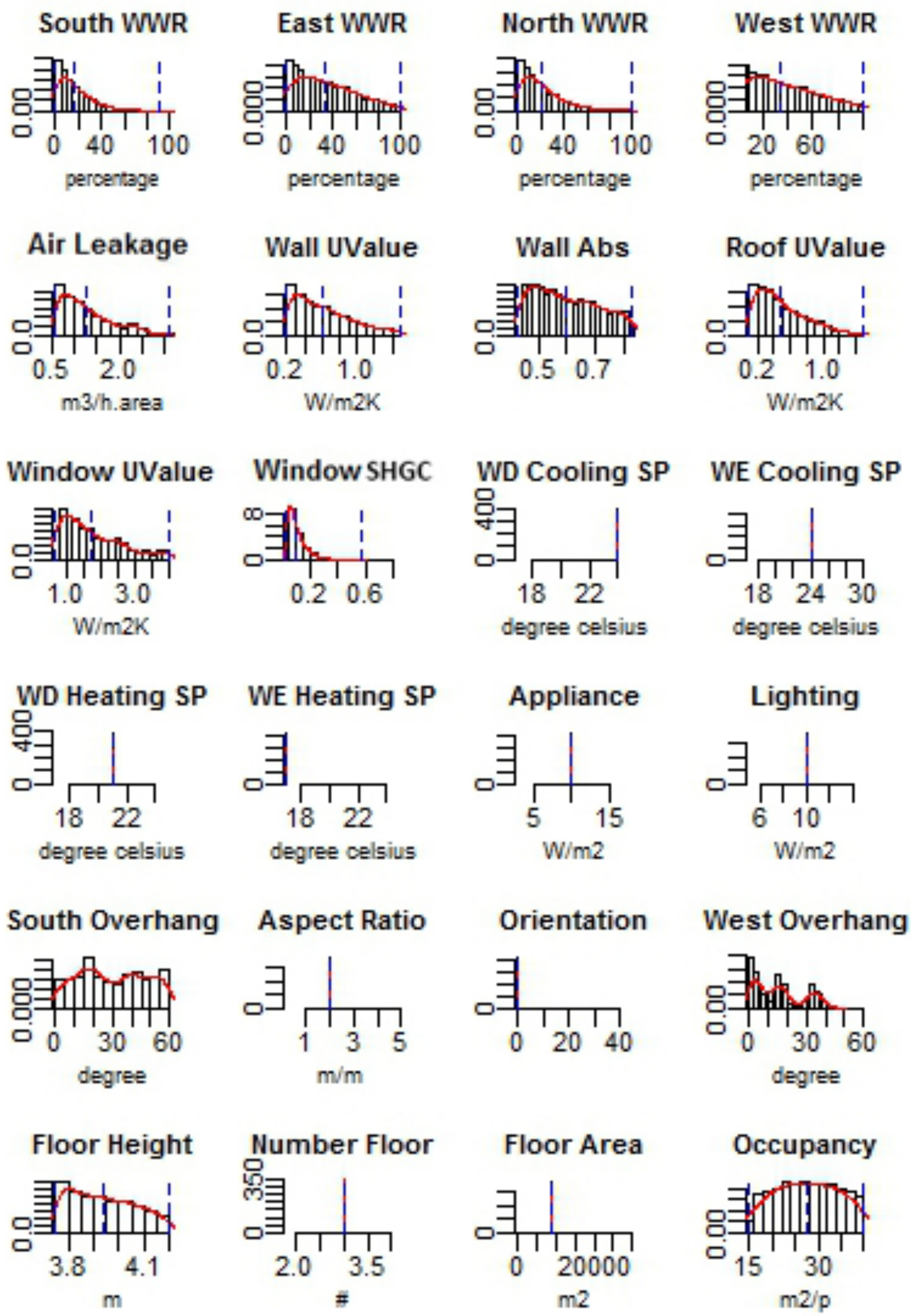


Figure 5.14(d) Atlanta case study; design scenario Atlanta _3-1

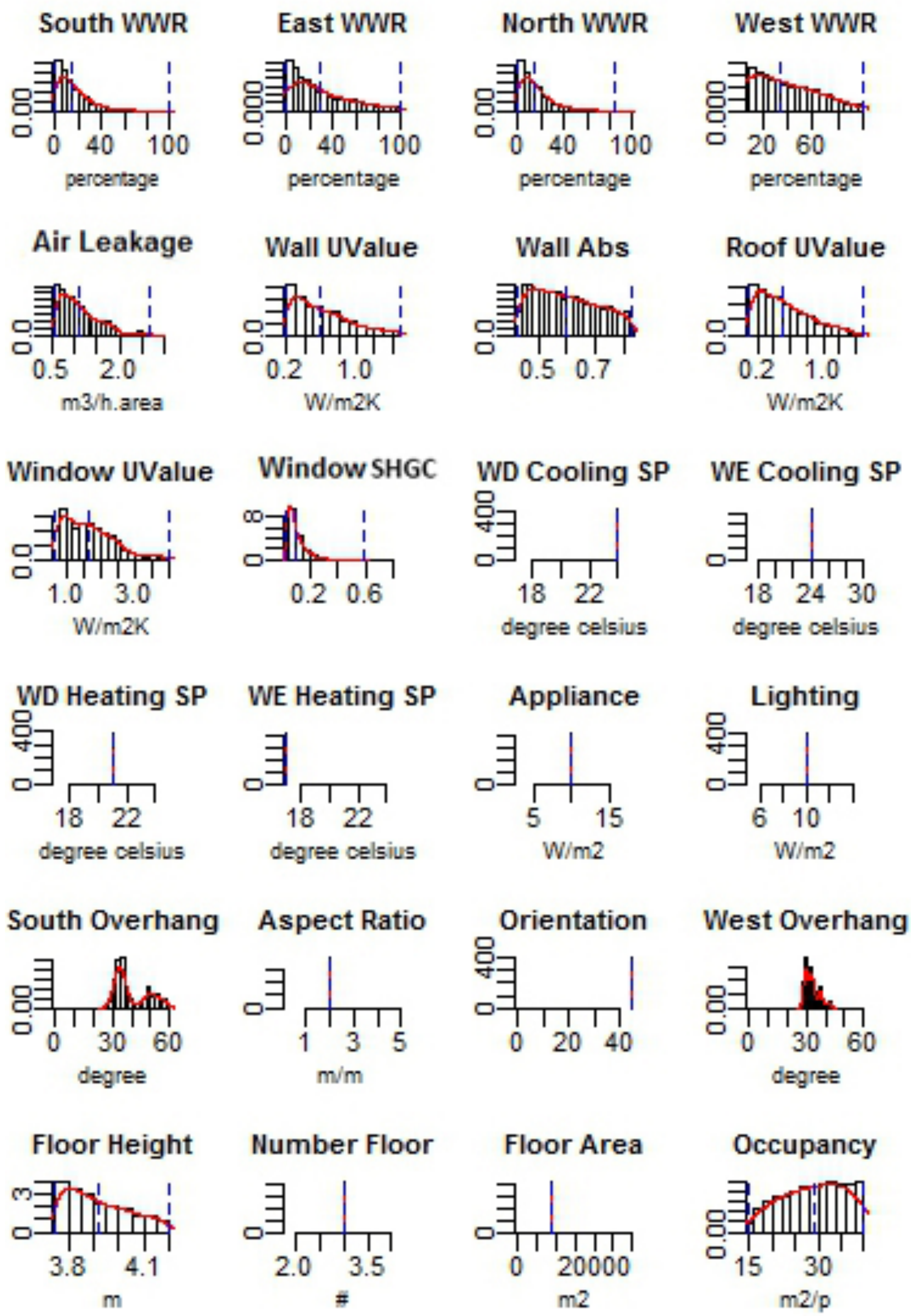


Figure 5.14(e) Atlanta case study; design scenario Atlanta _3-2

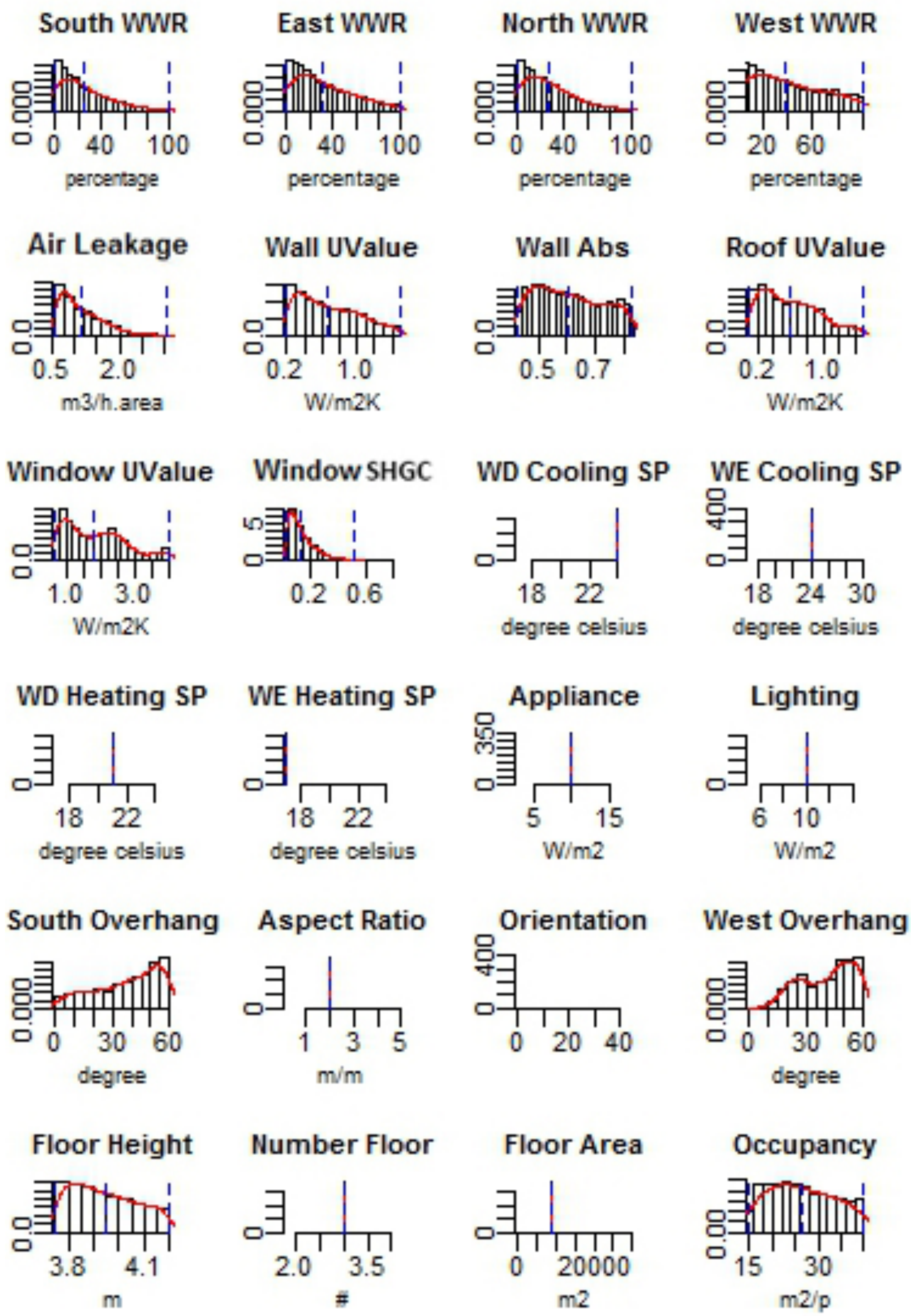


Figure 5.14(f) Atlanta case study; design scenario Atlanta _3-3

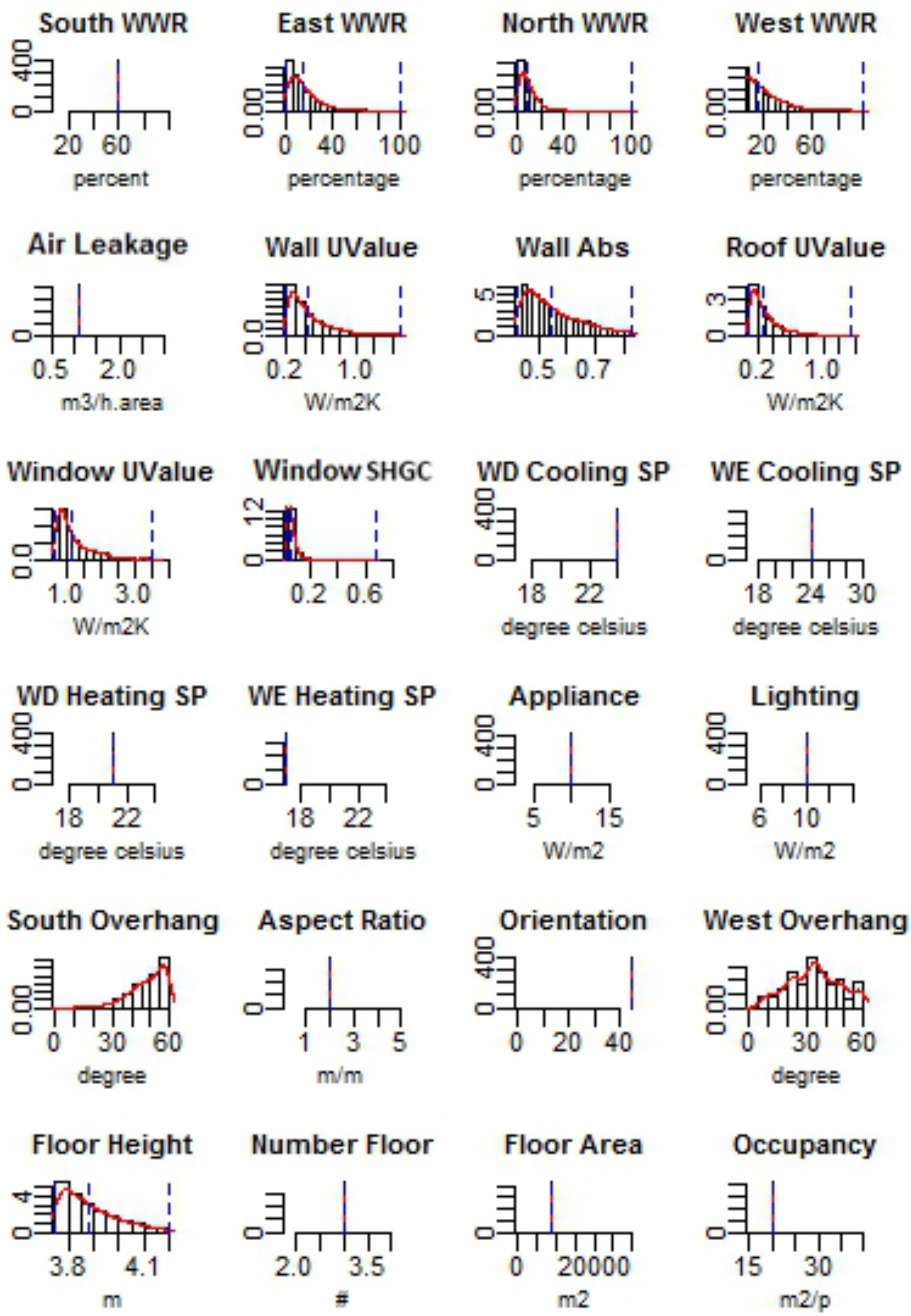


Figure 5.14(g) Atlanta case study; design scenario Atlanta _3-2-1

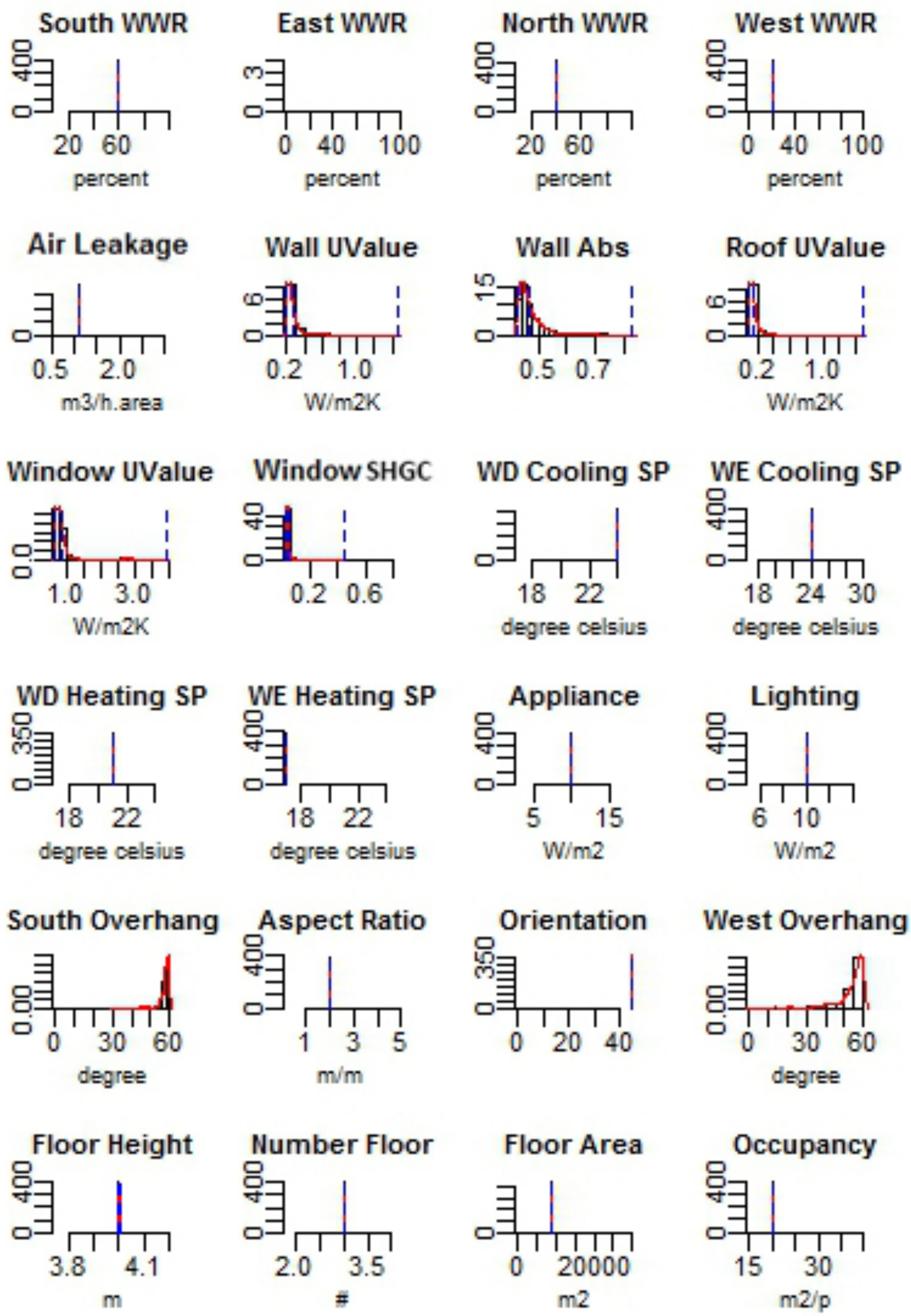


Figure 5.14(h) Atlanta case study; design scenario Atlanta _3-2-2

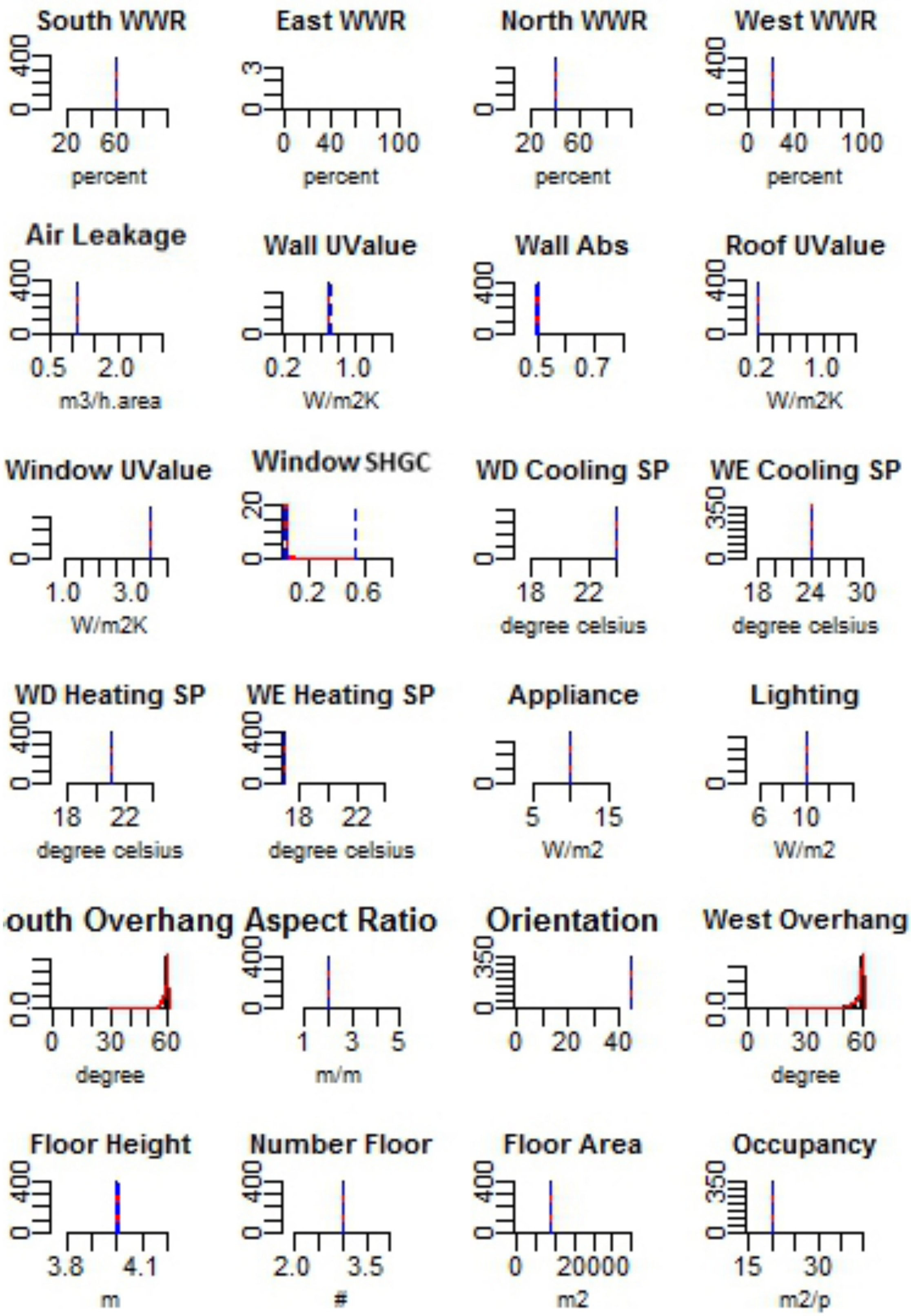


Figure 5.14(i) Atlanta case study; design scenario Atlanta _3-2-3

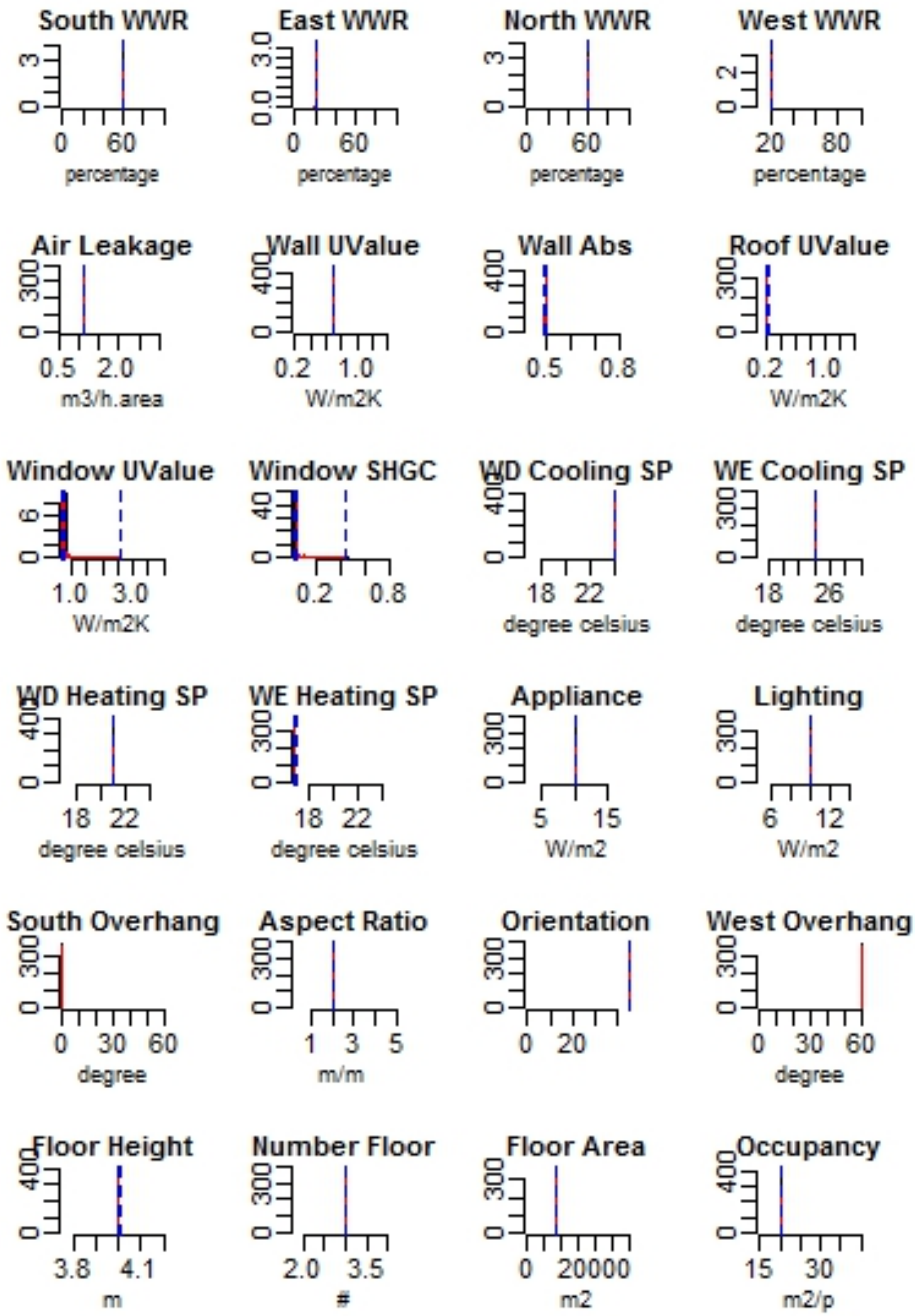
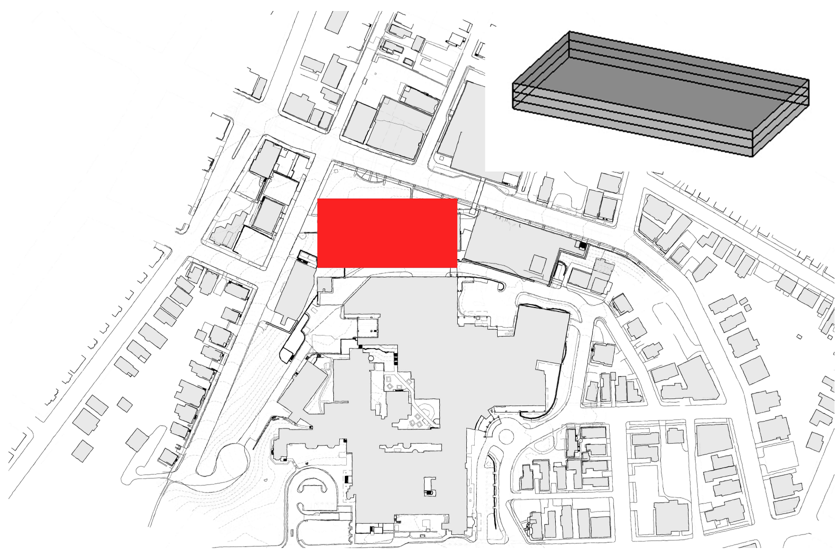
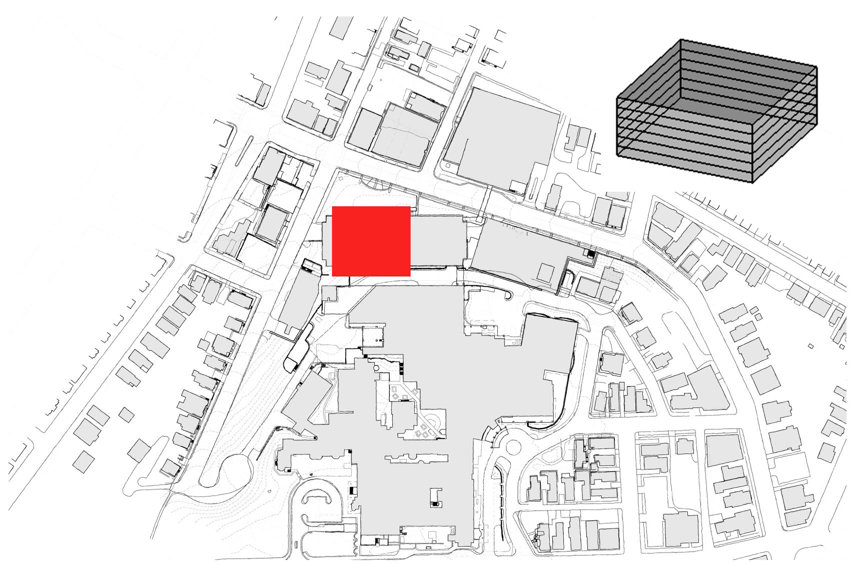


Figure 5.14(j) Atlanta case study; design scenario Atlanta _3-2-4

5.4. DESIGN OF MID-RISE OFFICE IN MIAMI

The final case study is a 15,000 square meter office building in Miami, and the first concern of the designers is either to spread the building mass more horizontally with less number of floors, or vertically with a lower floor area and higher number of stories. The site's configuration limits the buildings spread on east-west, but provides flexibility in north-south direction. By considering the required lighting and equipment loads and thermal setpoitnts, and assuming the width of the building to be fixed around 70 meters, three alternatives to compare are: three-story building with the floor aspect ratio of 2; six-story building with the aspect ratio of 1; and finally nine-story building with the aspect ratio of 0.66.





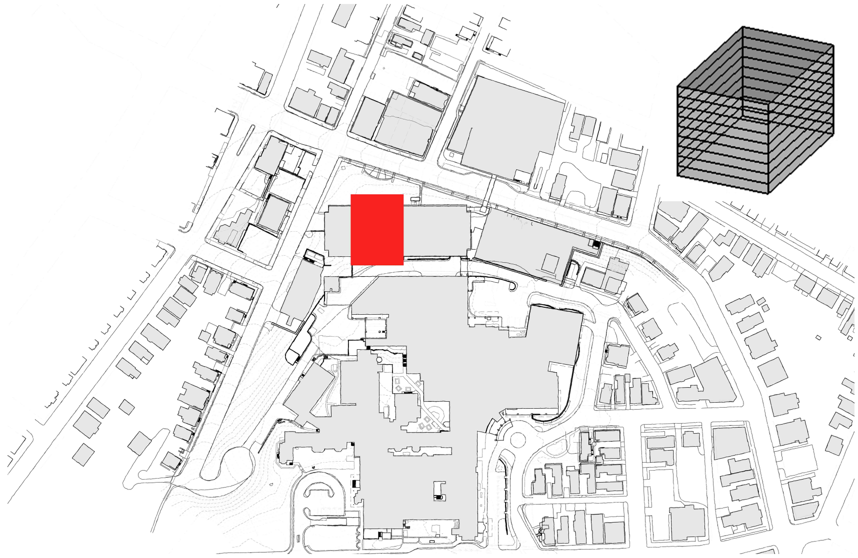


Figure 5.15 Medium-size office building in Miami with three mass alternatives

The histogram of thermal energy demand (response space histogram) for office building in Miami is shown in figure 5.16 along with the values of 10, 40 and 70 percentile of the data to be explored as three objectives in table 5.9. Table 5.10 shows the lists of design scenarios for this case study. Going from option Miami_3-1 to option Miami_3-3, the results of the inverse analysis shows more restrictions on the rest of the parameters (undecided parameters). It implies that designer would have more freedom and higher possibility of achieving their thermal energy performance if goes with the first option, and they encounter more restrictions in undecided parameters if goes with option 3.

After applying requirements of floor height and the opening on the south façade, and estimating the air-tightness of the building, the designers will make decision gradually upon the rest of the parameters and each sets of result guide him the design options for the next step.

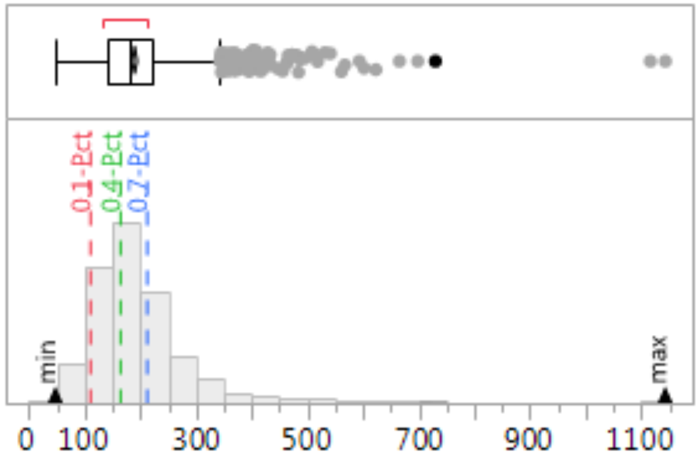


Figure 5.16 Histogram of thermal performance for office buildings in Miami

Table 5.9 Thermal performance possibilities for office building in Miami

Case Study	***Min***	***10 percentile***	***40 percentile***	***70 percentile***	***Max***
CS4-Miami	45.3	108.51	162.82	210.16	1143.4

Table 5.10 Design scenarios for the case study of Miami office building

STEP I		**STEP II**			**STEP III**	
Scenario	**Objective**	**Scenario**	**Constraints**	**Alternatives**	**Scenario**	**Iterative process of making decision**
Miami_1	Thermal load<=210.16					
Miami_2	Thermal load<=162.82					
Miami_3	Thermal load<=108.51					
		Miami_3-1	Floor area=15000, Orientation=1, Setpoints=(21, 16, 24, 28), Appliance=8, Lighting=10	#floor=3, AR=2		
		Miami_3-2	Floor area=15000, Orientation=1, Setpoints=(21, 16, 24, 28), Appliance=8, Lighting=10	#floor=6, AR=1		
		Miami_3-3	Floor area=15000, Orientation=1, Setpoints=(21, 16, 24, 28), Appliance=8, Lighting=10	#floor=9, AR=0.66		
					Miami_3-1-1	F_Height=4, Occupancy=25, Air leackage=1.5, SWWR=0.8
					Miami_3-1-2	EWWR=0.15, NWWR=0.4, WWWR=0.15,
					Miami_3-1-3	Window-SHGC=0.15, Wall-UValue=0.5, Roof-UValue=0.2
					Miami_3-1-4	South-Overhang=60, West-Overhang=60

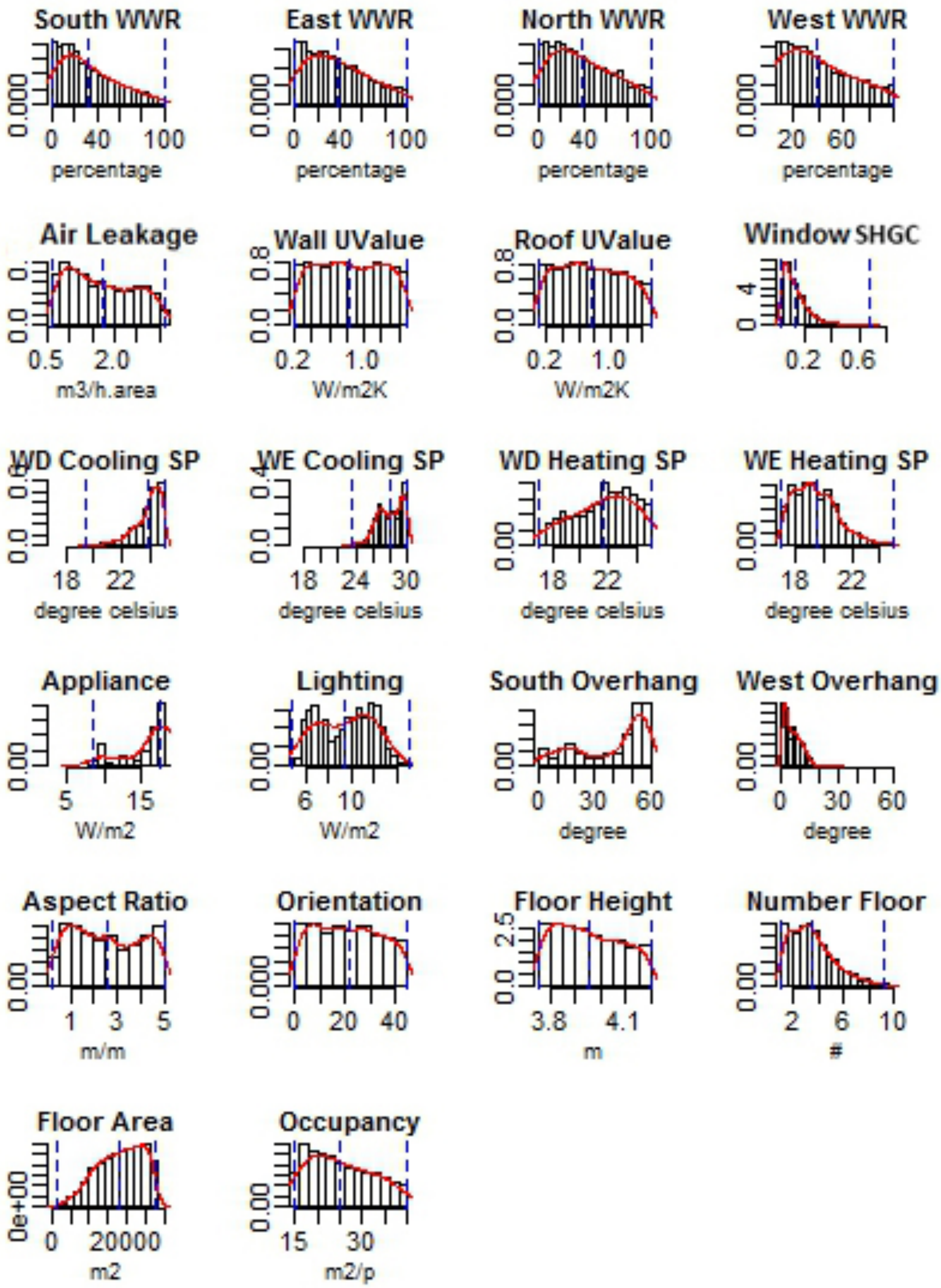


Figure 5.17(a) Miami case study; design scenario Miami_1

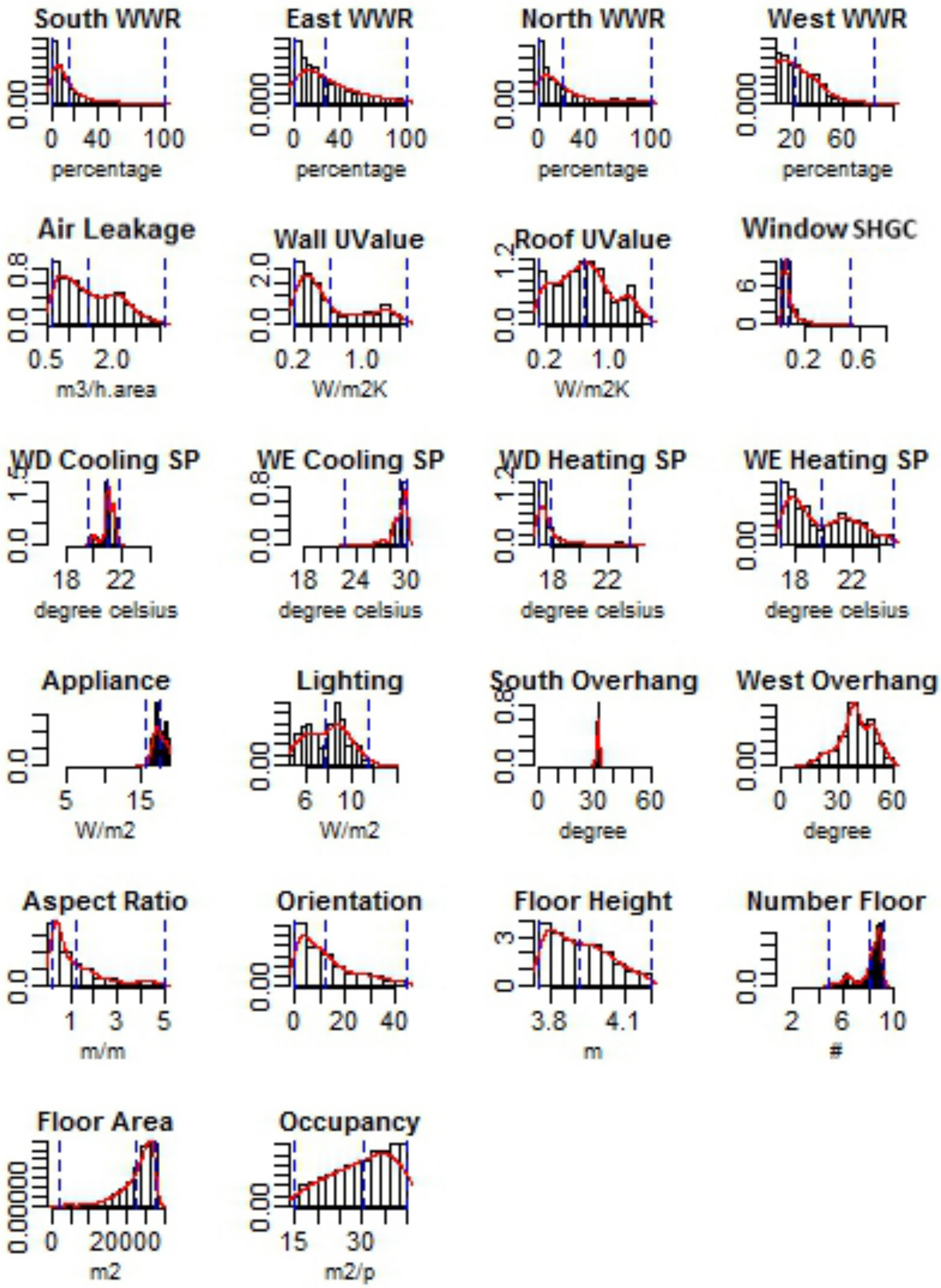


Figure 5.17(b) Miami case study; design scenario Miami_2

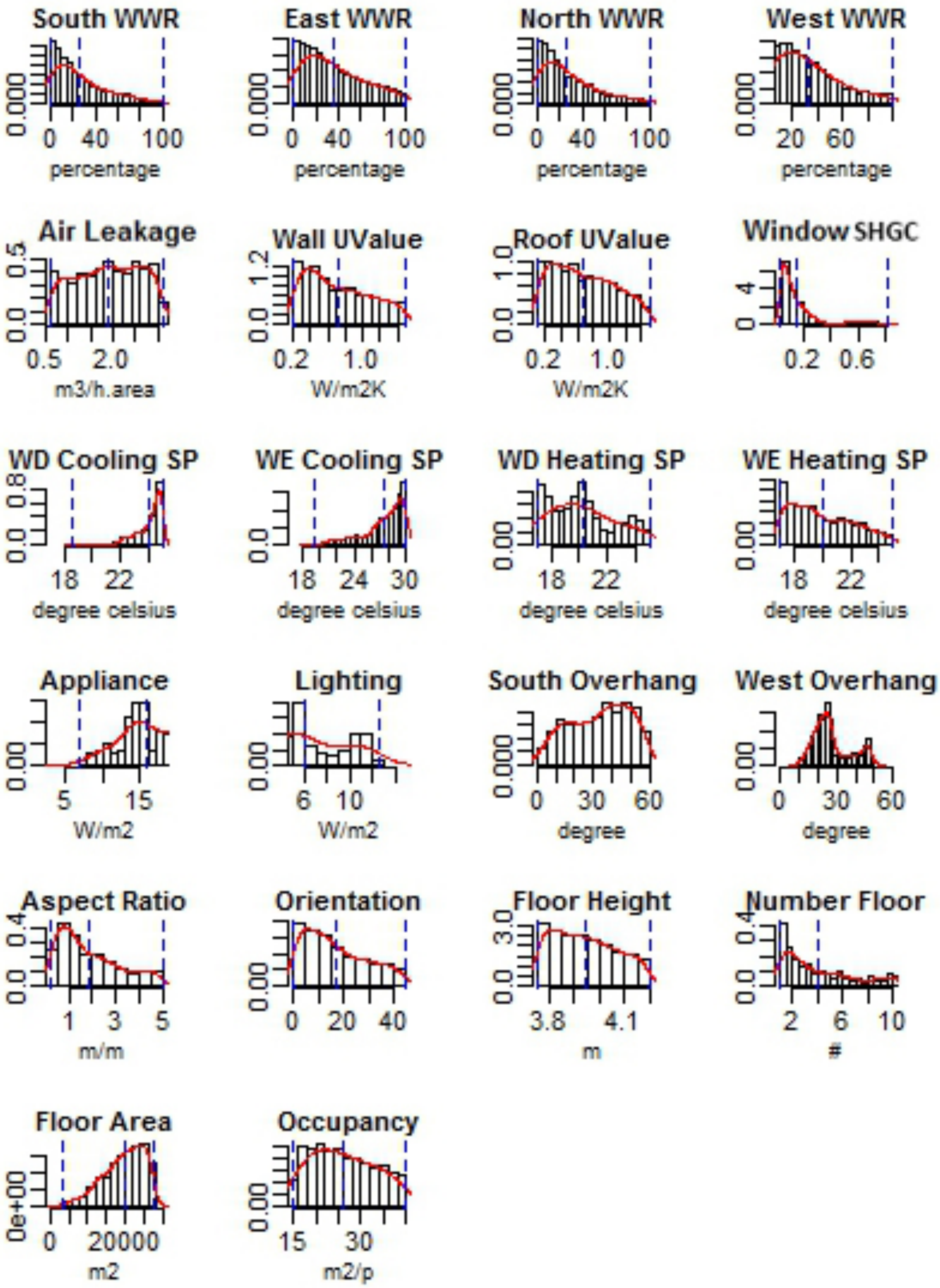


Figure 5.17(c) Miami case study; design scenario Miami_3

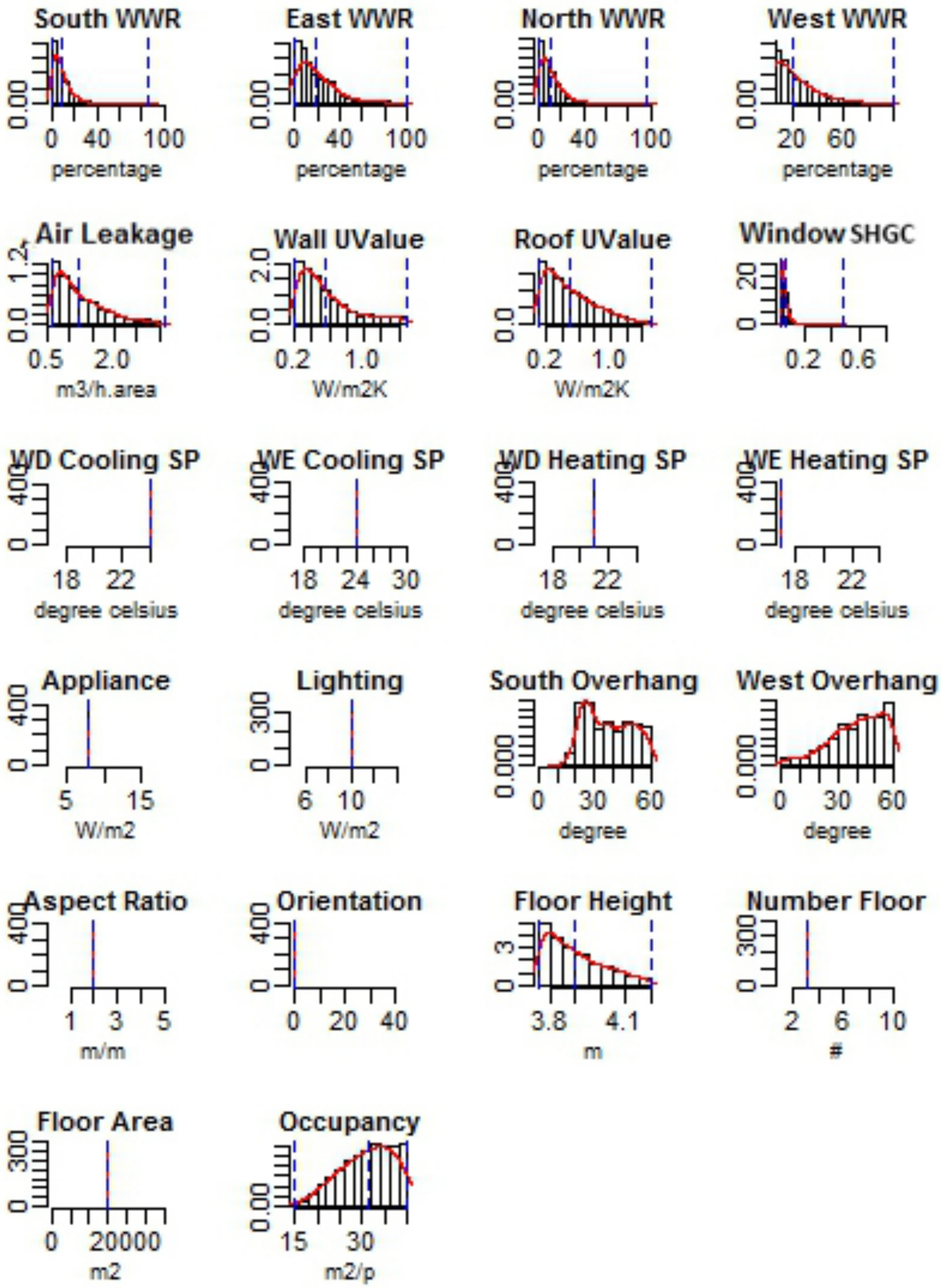


Figure 5.17(d) Miami case study; design scenario Miami_3-1

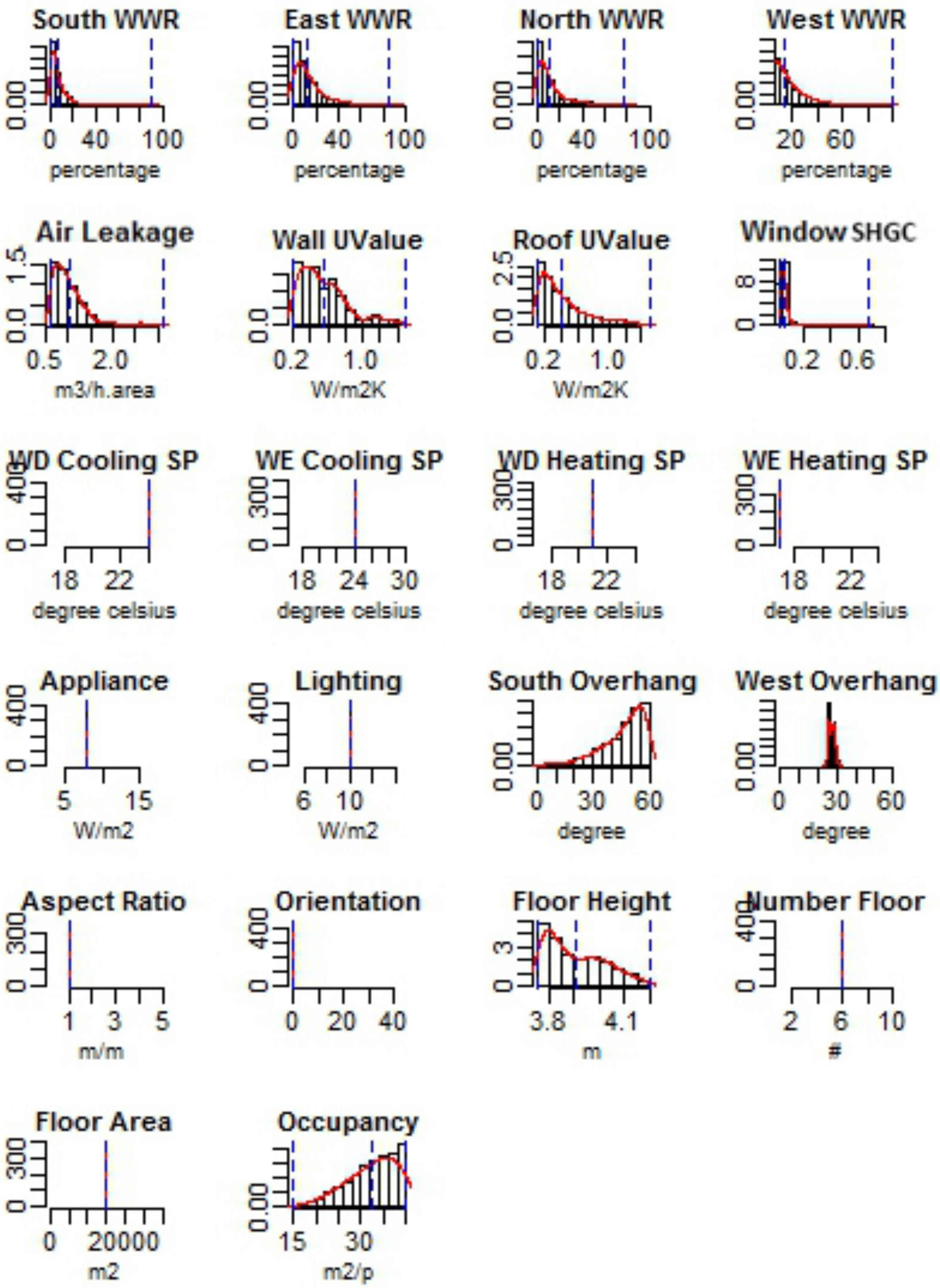


Figure 5.7(e) Miami case study; design scenario Miami_3-2

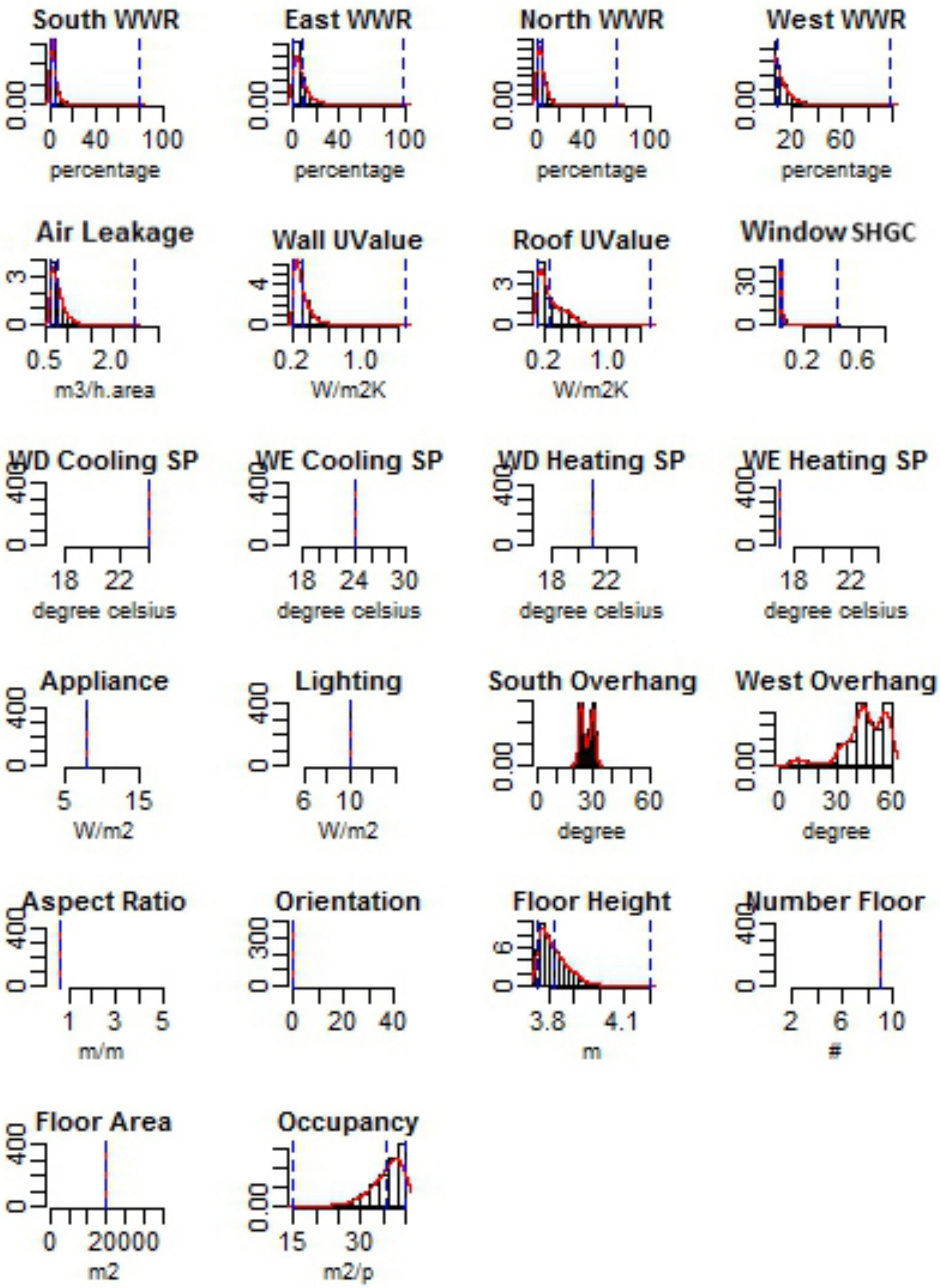


Figure 5.17(f) Miami case study; design scenario Miami_3-3

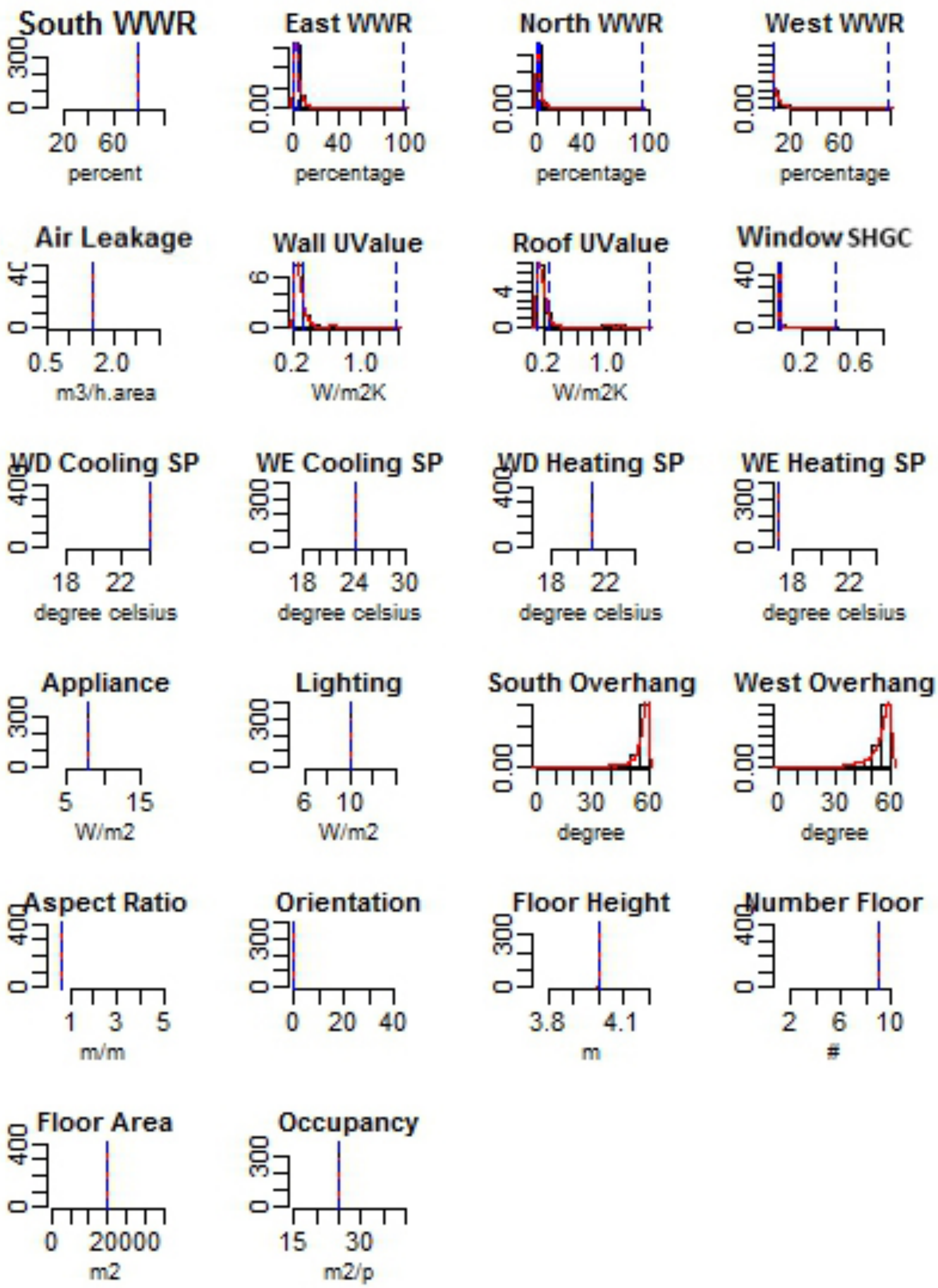


Figure 5.17(g) Miami case study; design scenario Miami_3-1-1

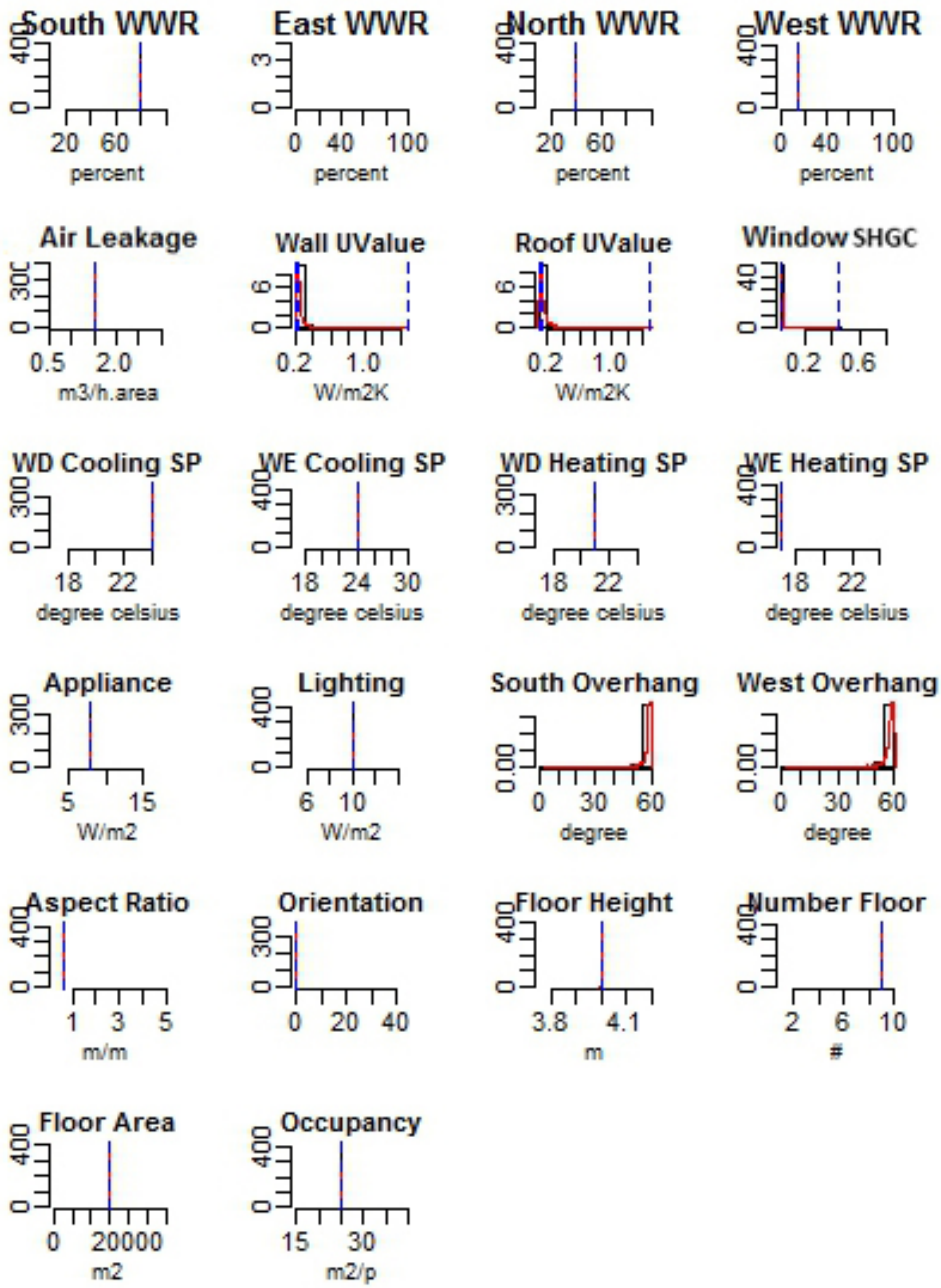


Figure 5.17(h) Miami case study; design scenario Miami_3-1-2

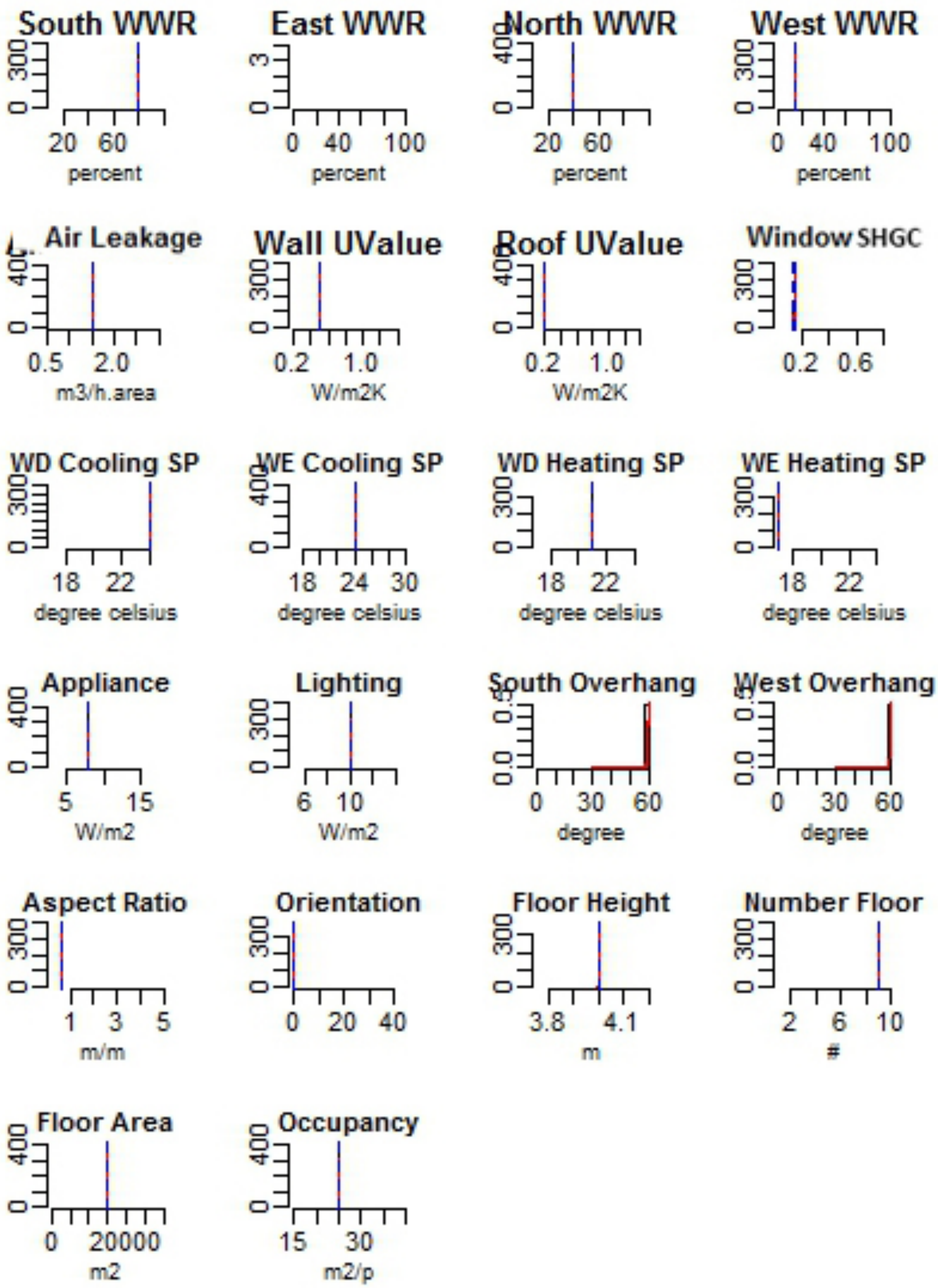


Figure 5.17(i) Miami case study; design scenario Miami_3-1-3

5.5. DISCUSSION

In this chapter, we have practiced the proposed inverse modeling approach for making decision regarding energy performance in four case studies at their early stage of design. At the very beginning, before any analysis is run, designers perceive the most significant design parameters affecting their design, based on the location of the building as well as its function. Although a large number of these specified design parameters were expected to be important, the Chicago elementary school, for example, shows that the building orientation is not among the most significant parameters regarding energy performance; the wall and roof U-values are not affecting the thermal load in Los Angeles school at the early stage of design comparing to other design parameters, and the window U-value is suggested to have a higher value; and finally in contrast to the common assumption, the window U-value of office buildings in Miami does not have a high impact on the thermal load. In addition to get knowledge of the most significant parameters, designers are also exposed to the possible range of resulting energy performance associated to their design, and are able to define the preferred energy performance objective more informedly

As seen in all case studies, we have started from defining energy performance objective (sum of heating and cooling load), and gradually have made decision about design parameters, based on the projects' requirements, constraints, and designers preferences. At the three first design scenarios, CS_1 to CS_3 in all case studies, when the parameters' design option spaces are in the maximum range and none of the parameters constraints have been implemented, assigning three different energy performance objectives does not result in observable differences in solution spaces. In other words, the probability distributions of design parameters resulting from any of three strict, intermediate, and conservative energy performances objective are not tangible; the reason is that at these very early scenarios, when none of the parameters have been decided upon, the level of undecided uncertainty is at its most, and it's hard to make any meaningful decision for the parameters, particularly when there are high level of interdependencies between parameters. But as the values of some of the parameters starts to be defined with a single value, which represents the requirement or constraints of the project is implemented or that parameter is decided upon, we see more tangible differences in the design solution spaces.

In the next set of design scenarios exploration, when the energy performance objective is specified, a few design parameters are defined, and designers are comparing three design alternatives (CS_3-1, CS_3-2, and CS_3-3 in all case studies), we will generally get more guidance for the solution spaces (more limited solution space) in comparison to the first design scenarios; comparing the solution spaces between the three design alternative CS_3-1, CS_3-2, and CS_3-3 depend on the projects characteristics and requirements at that stage of decision making; when there is no visible differences between the solution spaces associated with three alternatives, it means that the design team has a high level of freedom to choose any of those alternatives with confidence and a more concrete decision should be made at the later stages; the more visible differences between the resulting solution spaces means the high level of importance of the decision at that specific stage of design. In the Miami office case study, for example, the solution space associated with design alternative Miami_3-3 has more limitations and restrictions on the undecided parameters in comparison to alternatives Miami_3-2 and Miami_3-1, suggesting that designers' freedom for the rest of the parameters are limited in order to fulfill the energy objective. It means that designers would have higher possibility of achieving their thermal energy performance with many solution if goes with the first alternative, Miami_3-1, and they encounter more restrictions in undecided parameters if goes with Miami_3-3.

In the later design scenarios, when many parameters are decided (design scenarios of CS_3-j-k), the probability distributions of the parameters showing the solution spaces gradually gets lower diversion, meaning that the solution space for those parameters are more limited and suggests selecting the mean values of the distributions. In other words, going with the mean values have a higher chances of getting to the desired energy performance. But at the same time the distributions in the solution space represent the high number of possibilities for choosing design parameters while it is bounded to the energy performance objective. As discussed in the methodology chapter we also expect from inverse modeling, we do not look for the one best solution; instead we look to explore the whole solution space in which we sequentially choose our design parameters based on the requirements.

By defining a particular energy performance objective, this exercise also showed how the design parameters can change as a result of different design scenarios, and how design team can practice the trade-off between design options. In the Atlanta office building case study, for example, the solution space at the last design scenario (Atlanta_3-2-4) suggested having large shading devices at south, which aesthetically was not favored by the design team. By modifying the last scenario and considering the south shading devise as a decided parameter (value of zero) and window properties as undecided parameters, the design team got a new trade-off solution for glazing easily; this trade-off study and finding the best solution for glazing in current forward approach is often implemented through many trial and error for different glazing options, or through optimization, both of which cannot be compared with our proposed approach in terms of required time, computation, and easiness.

These examples showed the capability of the proposed approach to enhance the design knowledge by assisting designers to explore the design space, understand the significant parameters and their relationship, examine different design scenarios easily, and study the trade-offs quickly. In addition, the proposed inverse modeling approach provided flexibility and freedom for designers to adjust their design decision for different scenarios while still meeting the desired energy performance. And finally by incorporating the uncertainties and considering the concept of probability, this method brought robustness into the design process to make the decision less insensitive to other decisions that may occur in the later stages of design. The next chapter is dedicated to the validation of such proposed method.

CHAPTER 6

VALIDATION

Due to the lack of proper method for informed exploration of building design space at the early stage of design, we proposed a method based on linear inverse modeling that provided design exploration capability, and we tested its application in four case studies. Now in order to verify this method, or any other design decision making method, one should have two different levels of validation: (1) validation of the output of the proposed strategy as a design *product*, (2) validation of the proposed design *process* method. In other words, any proposed design method should be tested to see if its results are accurate and reliable, and if compared to other method, this method can help designers in a design process. Accordingly, and by considering the three main hypotheses defined in this study, the corresponding questions for validation can be formalized as:

1- *Are the solutions of the proposed inverse problem valid candidates to meet stakeholder preference and objective?*

2- *In comparison to the current prescriptive approach, does the proposed performance-based method help designers with the design process by providing more design freedom and guidance?*

3- *In comparison to the current prescriptive approach, does the proposed performance-based method give designers more confidence and lead them to a higher probability of achieving the performance objective?*

In order to answer the first question, we validate the accuracy of the proposed method results based on the definition of model validity by Hazelrigg (Hazelrigg 2003); he describes model validity in a design decision context, not in terms of an accurate estimation of an unrealized reality, but in terms of an accurate decision. As Hazelrigg describes:

> *"A model is valid if, when used in a specific decision making situation with a given set of available alternatives and the decision maker's beliefs and preferences, the decision maker is certain that his preferred choice is the choice that indeed yields the outcome that is most preferred from among the outcomes that could have been obtained from the set of available alternatives."*

Therefore, the first question is going to be answered in chapter section 6.1 by implementing forward modeling energy performance assessment; we are going to prove that the estimation of the design parameters resulted from the proposed method will lead us to the energy performance objective with defined level of confidence. This issue is justified by the definition of model validity by Hazelrigg, as the design method that leads to the designers' preferred outcome.

Provided that the first question is valid, the next step is to test the advantage of this method compared to the current design decision-making approaches. As repeatedly mentioned before, a good method for design exploration and decision making is the one that help designers in both divergent phases, for generating more promising options, and convergent phases, for higher chances of selecting better design. Since to our knowledge the design industry lacks a proper method for design generation regarding energy performance, and the building energy codes and standards are considered as guidelines for design parameters generation, we are going to test the proposed method with the ASHRAE 90.1-2013 as the prescriptive method. Consequently, question 2 and 3 are explored by comparison to the guidelines associated with ASHRAE in sections 6.2 and 6.3.

6.1. VALIDATION OF HYPOTHESIS I

In order to scientifically explore question 1, all sets of estimated design parameters for each model (i.e. particular sets of value for x) found by inverse modeling will be analyzed using conventional forward modeling. In other words, we will develop the design experiments adopting all case studies with the scenarios we have explored in previous chapter; in each of these tests, we sample from the design solution space, assess the energy performance by forward modeling using the normative model, and will get probability distributions of energy performance to explore if the results fulfill the predefined objective. The scenarios to be tested are:

- *Test Scenario 0 (TS_0)*: Probabilistic Bracketing- random sampling from the initial design option space– we run the forward modeling procedure, using the design parameters assuming they are uniformly distributed over their range. The result performance, y_{TS_0}, represents the energy profile (probability distribution) of all possibilities, which can be our comparison baseline.
- *Test Scenario 1* to *9 (TS_1* to TS_9): design scenarios solution space sampling – we get the solution space of design parameters in each design scenario in the form of probability distribution (the results of inverse modeling); we then sample from these spaces, and run the forward approach using normative model to come up with the energy performance profile, y_{TS_1} to y_{TS_9}.
- *Test Scenario 10 (TS_{10})*: we calculate the energy performance associated with the last iteration of each case study, or the final design decision, using the normative energy model. The results of this analysis will be represented deterministically as one value, $y_{TS_{10}}$.

Figure 6.1 graphically represents the design parameters' solution space we got from the previous chapter in four case studies, and figure 6.2 represents the process we implement for their validation.

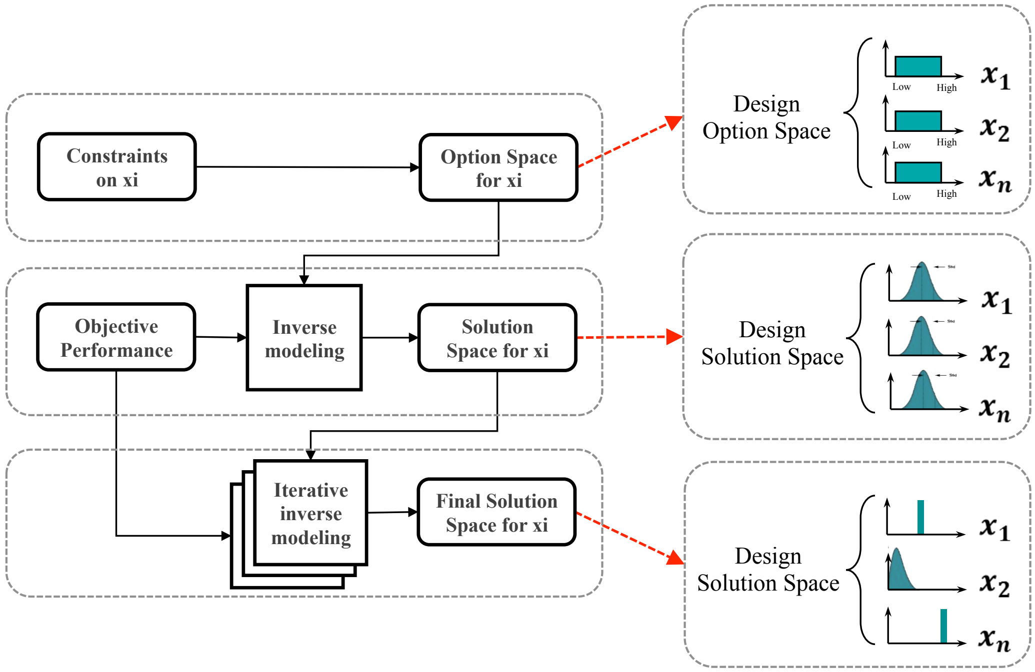


Figure 6.1 The process of iterative decision making using inverse modeling;

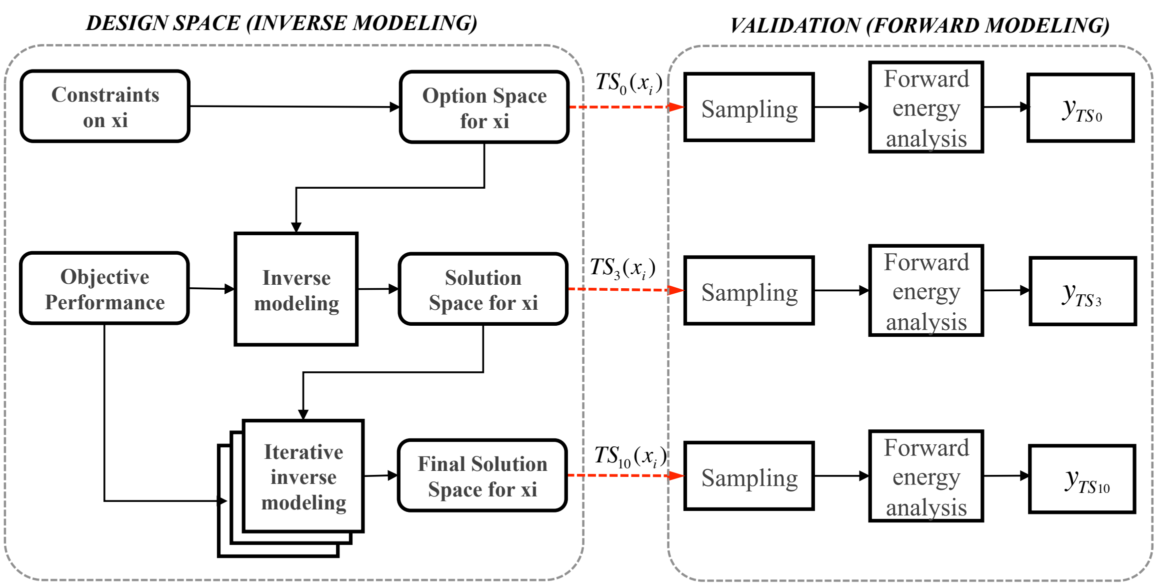


Figure 6.2 The process of output validation, using forward modeling in each test scenario

After applying the test scenarios to each case study, we evaluate the associated energy performance, y_{TS_i}, and explore how well the solution space in each scenario fulfills the energy performance objective. By assuming that the objective requires the energy performance to be equal or less than b, we would like to first prove that the probability of energy performance objective fulfillment is gradually increased going from design scenario 1 to 10; and we have enough level of confidence that the last design scenario fulfills the energy performance objective. In other words, we are expecting to have a result as figure 6.3.

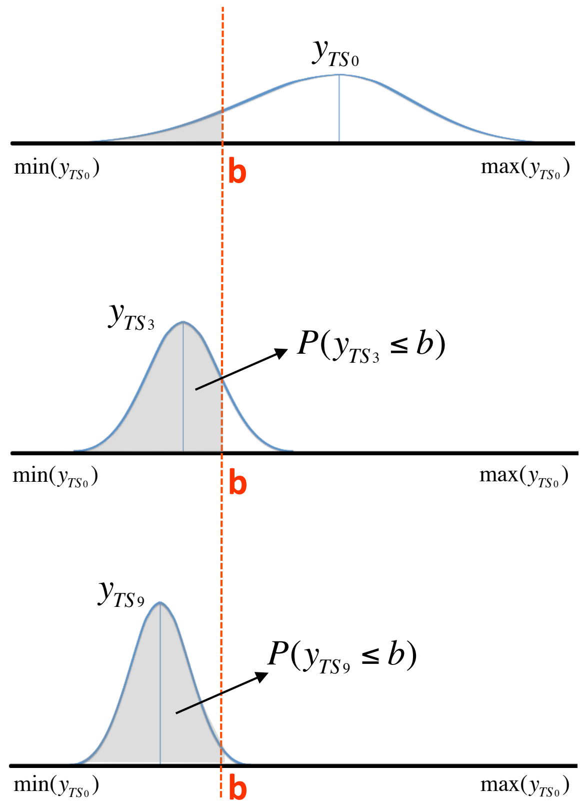
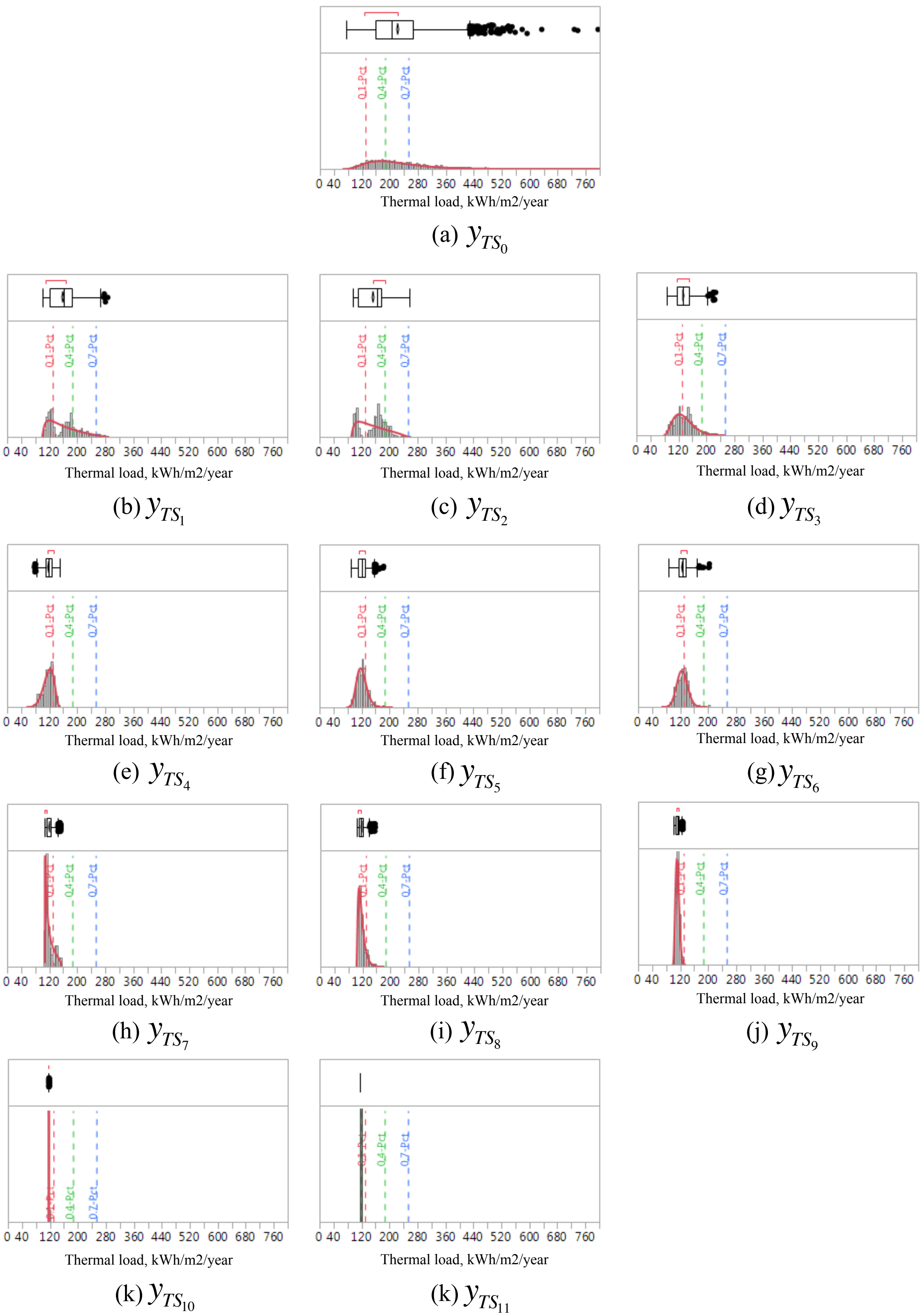


Figure 6.3 Validation by comparing the expected thermal performance of each test scenario

6.1.1. Validation Results for Four Explored Case Studies

After sampling from all design parameters' solution spaces we have from four case studies (nine or ten solution spaces in each case study), and calculating their energy performance using the normative EPC energy model in forward mode, the resulting energy performance distributions are presented in figure 6.4 to 6.7, and the corresponding values are listed in tables 6.1 to 6.4.



(a) y_{TS_0}

(b) y_{TS_1} (c) y_{TS_2} (d) y_{TS_3}

(e) y_{TS_4} (f) y_{TS_5} (g) y_{TS_6}

(h) y_{TS_7} (i) y_{TS_8} (j) y_{TS_9}

(k) $y_{TS_{10}}$ (k) $y_{TS_{11}}$

Figure 6.4 The energy performance distributions of design scenarios associated with case study CS1_Chicago elementary school

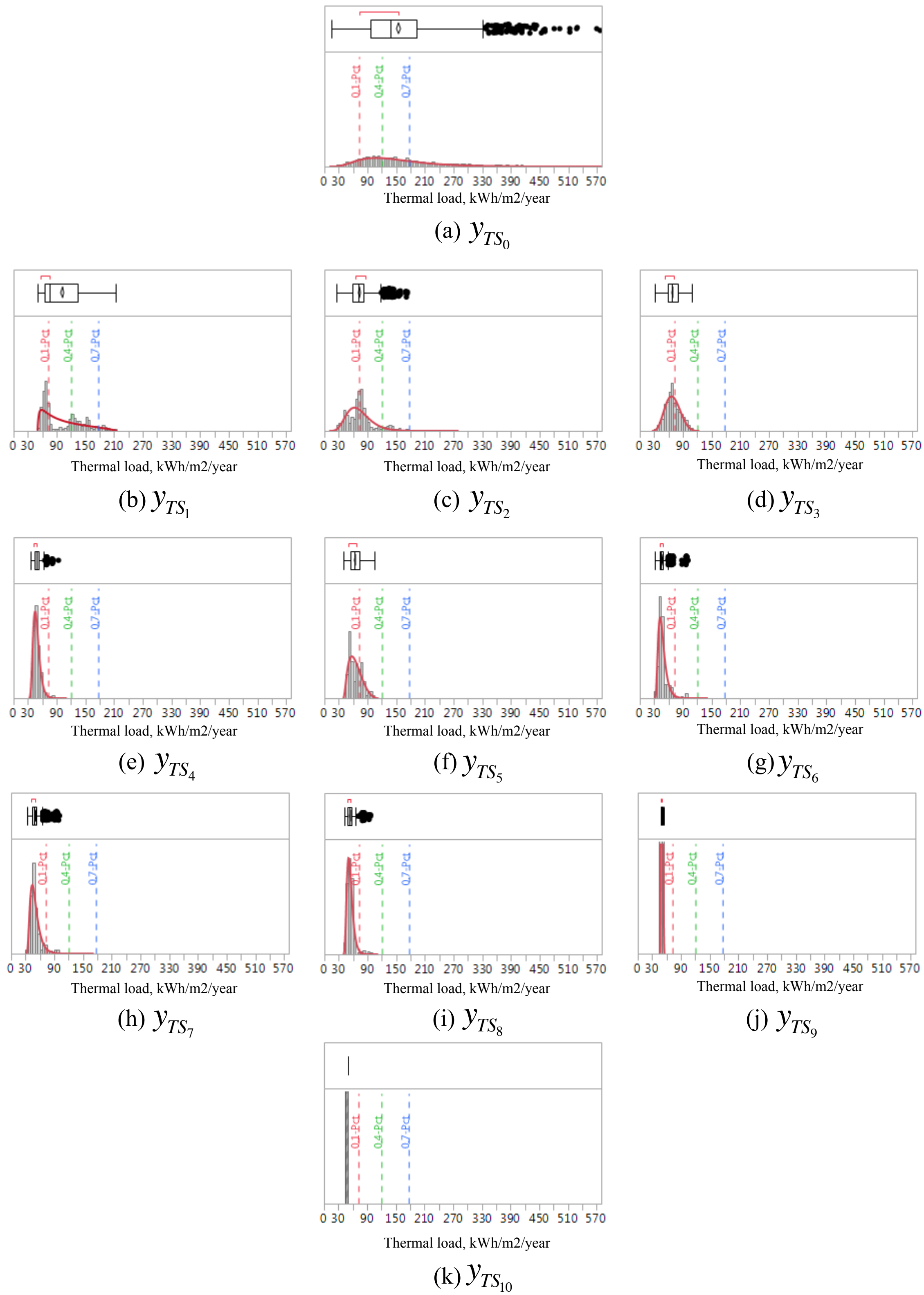


Figure 6.5 The energy performance distributions of design scenarios associated with case study CS2_Los Angeles elementary school

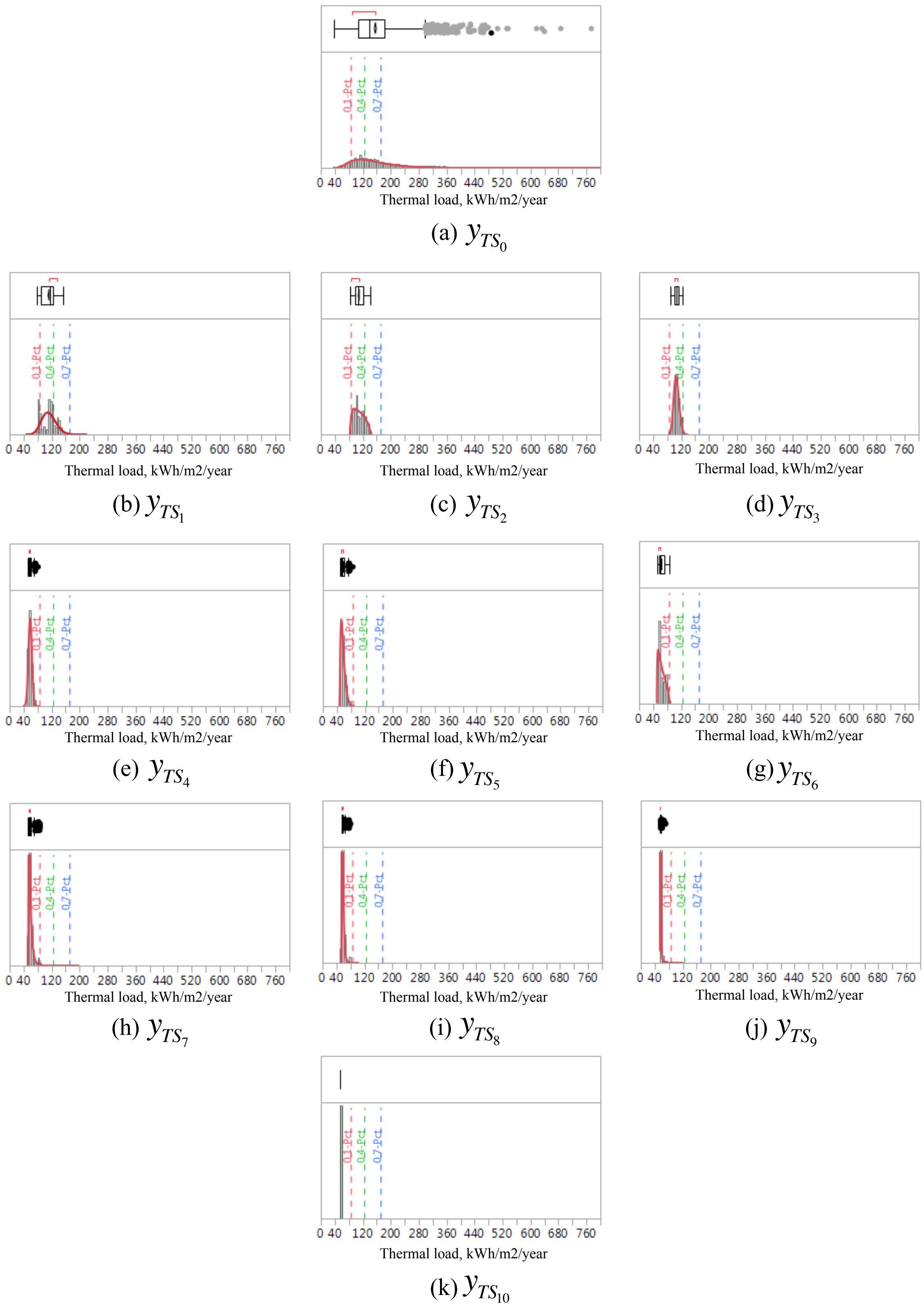


Figure 6.6 The energy performance distributions of design scenarios associated with case study CS3_Atlanta mid-size office building

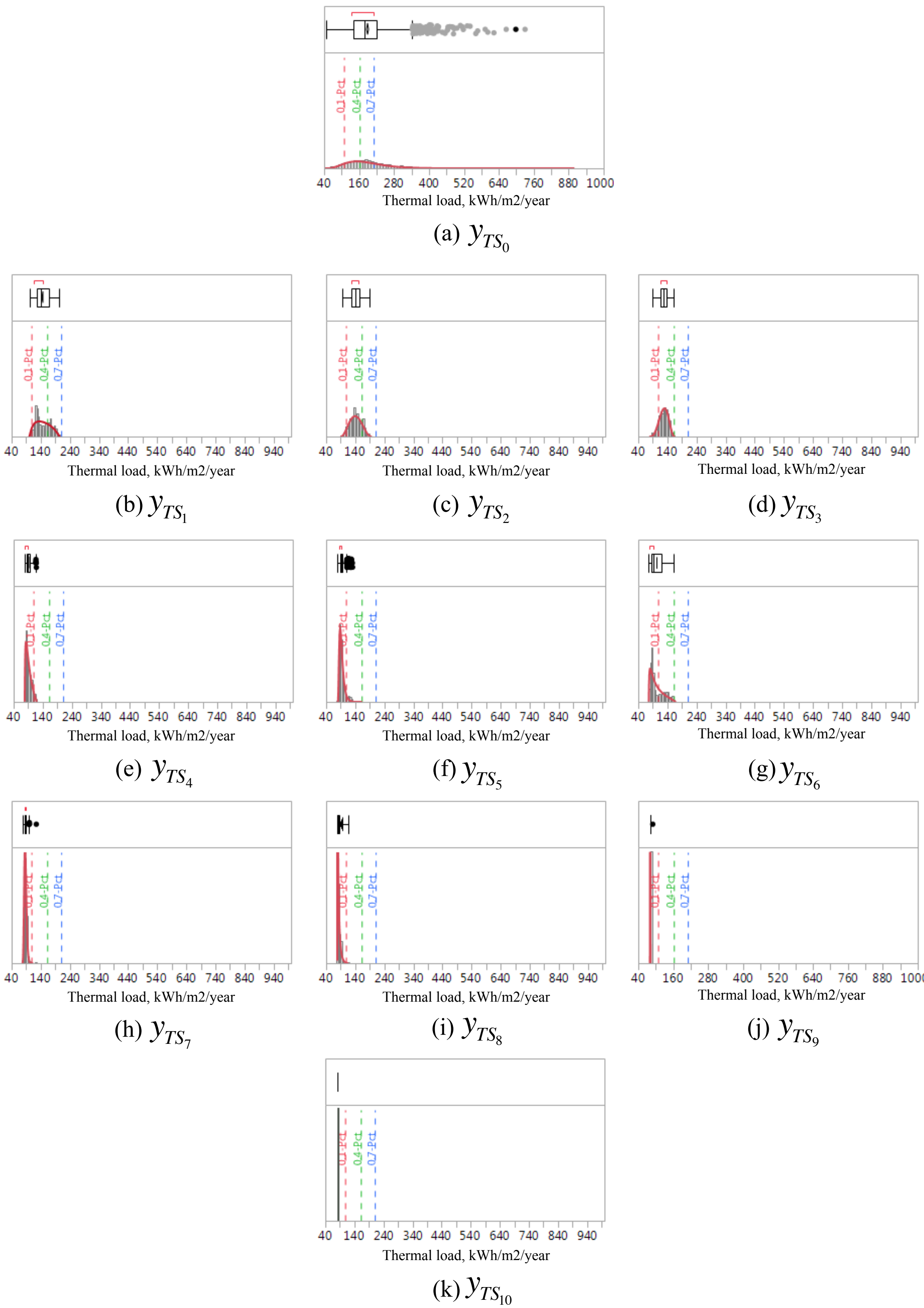


Figure 6.7 The energy performance distributions of design scenarios associated with case study CS4_Miami mid-size office building

Table 6.1 Hypothesis I validation, Chicago primary school case study

Chicago Primary School		Min	Max	Mean	Std Dev	Std Err Mean	Objective	Fulfillment Percentage 0.1 percentile= 130.61 0.4 percentile= 186.79 0.7 percentile= 253.76
	Whole design space	75.85	795.29	222.23	86.43	1.93	-	-
PHASE I	TS-1	101.12	287.24	159.31	39.74	1.25	y_{TS} <= 253.76	97.9%
	TS-2	94.20	255.76	152.37	35.47	1.12	y_{TS} <=186.79	84.9%
	TS-3	85.61	226.66	134.15	26.35	0.83	y_{TS} <=130.09	47.8%
PHASE II	TS-3-1	78.07	148.83	117.40	14.49	0.45	y_{TS} <=130.09	81.4%
	TS-3-2	88.10	184.69	120.77	14.76	0.46	y_{TS} <=130.09	78.5%
	TS-3-3	85.25	203.60	125.80	15.34	0.48	y_{TS} <=130.09	58.0%
PHASE III	TS-3-2-1	107.61	153.17	119.93	12.38	0.39	y_{TS} <=130.09	79.2%
	TS-3-2-2	103.64	157.60	117.33	9.74	0.30	y_{TS} <=130.09	87.9%
	TS-3-2-3	101.19	128.27	112.19	5.22	0.16	y_{TS} <=130.09	100.0%
	TS-3-2-4	116.78	117.85	116.84	0.13	0.00	y_{TS} <=130.09	100.0%
	TS-3-2-5_Final			116.95			y_{TS} <=130.09	100.0%

Table 6.2 Hypothesis I validation, Los Angeles primary school case study

Los Angeles Primary School		Min	Max	Mean	Std Dev	Std Err Mean	Objective	Fulfillment Percentage 0.1 percentile= 72.28 0.4 percentile= 120.35 0.7 percentile= 177.92
	Whole design space	14.37	576.57	155.26	81.79	1.82	-	10.0%
PHASE I	TS-1	50.08	212.98	101.96	42.55	1.34	y_{TS} <=177.92	94.0%
	TS-2	25.99	173.48	73.41	26.58	0.84	y_{TS} <=120.35	91.9%
	TS-3	31.55	108.53	68.63	15.11	0.47	y_{TS} <=72.28	72.1%
PHASE II	TS-3-1	35.03	93.90	48.25	7.47	0.23	y_{TS} <=72.28	98.8%
	TS-3-2	40.13	104.00	64.58	13.22	0.41	y_{TS} <=72.28	70.5%
	TS-3-3	31.56	100.93	47.28	10.07	0.31	y_{TS} <=72.28	98.1%
PHASE III	TS-3-2-1	33.12	101.07	50.26	11.54	0.36	y_{TS} <=72.28	94.2%
	TS-3-2-2	41.06	96.61	53.76	7.34	0.23	y_{TS} <=72.28	96.9%
	TS-3-2-3	47.11	54.82	50.39	1.67	0.05	y_{TS} <=72.28	100.0%
	TS-3-2-4_Final			49.87			y_{TS} <=72.28	100.0%

Table 6.3 Hypothesis I validation, Atlanta office building

Atlanta Med-Office		Min	Max	Mean	Std Dev	Std Err Mean	Objective	Fulfillment Percentage 0.1 percentile= 85.34 0.4 percentile= 124.35 0.7 percentile= 171.07
	Whole design space	36.81	774.06	155.70	75.46	1.73	-	10.0%
PHASE I	TS-1	78.46	154.10	112.08	19.97	0.63	y_{TS} <=171.07	100.0%
	TS-2	83.39	142.51	108.88	14.76	0.46	y_{TS} <=124.35	81.9%
	TS-3	58.63	124.86	102.71	9.58	0.23	y_{TS} <=85.34	22.1%
PHASE II	TS-3-1	50.72	81.55	58.61	5.04	0.15	y_{TS} <=85.34	100.0%
	TS-3-2	47.74	85.78	57.24	6.14	0.19	y_{TS} <=85.34	99.9%
	TS-3-3	50.55	86.88	64.13	9.58	0.30	y_{TS} <=85.34	99.2%
PHASE III	TS-3-2-1	52.92	87.49	59.62	6.42	0.20	y_{TS} <=85.34	99.5%
	TS-3-2-2	53.68	80.64	58.08	3.79	0.12	y_{TS} <=85.34	100.0%
	TS-3-2-3	55.20	71.59	56.16	1.59	0.05	y_{TS} <=85.34	100.0%
	TS-3-2-4_Final			56.24			y_{TS} <=85.34	100.0%

Table 6.4 Hypothesis I validation, Miami mid-office building

Miami Med-Office		Min	Max	Mean	Std Dev	Std Err Mean	Objective	Fulfillment Percentage 0.1 percentile= 108.51 0.4 percentile= 162.82 0.7 percentile= 210.16
	Whole design space	45.31	1143.40	189.96	82.11	1.83	-	_
PHASE I	TS-1	100.65	202.70	146.93	24.97	0.78	y_{TS} <=210.16	100.0%
	TS-2	94.57	189.19	140.74	19.36	0.61	y_{TS} <=162.82	83.1%
	TS-3	79.13	162.13	127.10	14.51	0.45	y_{TS} <=108.51	13.7%
PHASE II	TS-3-1	77.91	117.97	90.73	9.06	0.28	y_{TS} <=108.51	95.2%
	TS-3-2	79.80	130.68	93.15	8.78	0.27	y_{TS} <=108.51	93.1%
	TS-3-3	74.84	162.13	102.24	22.84	0.72	y_{TS} <=108.51	68.3%
PHASE III	TS-3-2-1	78.16	124.55	87.14	4.04	0.12	y_{TS} <=108.51	99.9%
	TS-3-2-2	77.92	116.02	82.31	4.46	0.14	y_{TS} <=108.51	99.9%
	TS-3-2-3	80.26	89.51	80.76	0.28	0.01	y_{TS} <=108.51	100.0%
	TS-3-2-4_Final			80.26			y_{TS} <=108.51	100%

In all of the four test scenarios, going from y_{TS_1} to y_{TS_3}, we make the objective stricter, and therefore the expected value of energy performance distribution decreases:

$$E(y_{TS_3}) \leq E(y_{TS_2}) \leq E(y_{TS_1}) \qquad \text{Eq. (6.1)}$$

Since there are high level of undecided parameter uncertainties at the very beginning of the design and interdependencies between parameters, we have to have a sequential process of decision making to get the required performance with confidence.

Going from $\mathrm{y}_{\mathrm{TS}_4}$ to $\mathrm{y}_{\mathrm{TS}_6}$, we have some constraints on the design parameters and have compared three design options. As noticed in the case study results, comparing the alternatives at the stage when there are still many undecided parameters cannot be done with confidence. Unless we see a noticeable differences in the design parameter distributions, such as in the last case study on Miami, CS_4. Consequently, at this point we just can predict equation 6.2 because the design scenario 4, 5 and 6 have the same objective as design scenario 3, but with lower undecided parameter uncertainty:

$$P(y_{ST_4} \leq b), P(y_{TS_5} \leq b), P(y_{TS_6} \leq b) \geq P(y_{TS_3} \leq b) \qquad \text{Eq. (6.2)}$$

Design scenarios 7 to 9 are the ones that we are really interested in investigating the result for, because the number of undecided parameters has decreased and we should consider confidence in the energy performance fulfillment. At this point, in addition to having the energy performance distributions with lower standard deviation, we should also have enough level of confidence that the predicted performance fulfills the requirement. In other words,

$$\Pr\left((y_{TS_9}) \leq b\right) \geq \varphi \quad \text{for} \quad \varphi = 0.90 \quad (for\ example) \qquad \text{Eq. (6.3)}$$

where φ represnets the minimum confidence level to be satisfied, which will be measured based on the sums of the errors we have in each testing procedure. Talking about confidence and certainty, it is beneficial to review the errors we encounter in this method. The energy performance of the resulted testing procedures includes the following two types of error:

$$y_{TS_i} = f(x) + \boldsymbol{\varepsilon} + \boldsymbol{\theta}, \quad where \qquad \text{Eq. (6.4)}$$

$$\begin{cases} \boldsymbol{\varepsilon}: error\ related\ to\ the\ misfit\ btw\ linear\ model\ and\ normative\ model \\ \boldsymbol{\theta}: error\ related\ to\ the\ undecided\ parameter\ uncertainty \\ \boldsymbol{f(x)}: expectedenergy\ performance\ using\ forward\ modeling \end{cases}$$

Choosing the acceptable value for φ depends on these errors. In chapter four, we described how we minimized the first error, ε, or stakeholders preferred confidence by including it in the calculation of objective energy performance in inverse modeling. For the four cases studies, we had considered 90% confidence and reduced this error. The second error associated with the undecided parameter uncertainty is gradually decreased as decisions about any parameter are made. Subsequently, at the last design scenarios of

y_{TS_9} and $y_{TS_{10}}$, we should have the least amount of this type of error, and therefore have at least 90% confidence that the design fulfills the objective energy performance. As seen in four case studies results in tables 6.1 to 6.4, we have 100% confidence that our last decision-making scenario fulfills the objective energy performance. It should be noted that these levels of confidence have been calculated and achieved by considering undecided-parameters uncertainty. As mentioned in the second chapter of this study, we are not considering other types of uncertainties such as physical and scenario uncertainties due to their lower significance compared to undecided-parameter uncertainty.

6.2. VALIDATION OF HYPOTHESIS II

In addition to proving the outcomes of the proposed method to be valid, we have to prove that the proposed method is helping designers in design exploration and decision-making processes in comparison to current prescriptive methods. The idea is that if designers are provided with this proposed performance-based decision making method, it should increase their chances of developing promising concepts, and that in turn would increase the possibility of creating better products. Furthermore, a good approach is assumed to be the one in which designers are supported and encouraged to generate the widest possible range of concepts, to provide them with more design freedom and guidance in the divergent phases of design.

Chapter two of this study reviewed the current decision making methods regarding energy performance and the current reliance on prescriptive methods, particularly at the early stage of design. In contrast to the proposed performance-based approach that is subject to the preferences of designers regarding strictness of building energy performance, prescriptive methods such as ASHRAE 90.1 do not include any explicit performance objective. The codes and guidelines for a set of design parameters are provided in order to increase the possibility of having more energy efficient buildings. Consequently comparing the proposed inverse approach with prescriptive approach has been a big challenge. However, by considering a few assumptions, we have developed a platform these types of comparison for the validation. In the next two sections, we have chosen four prototype buildings suggested by ASHRAE 90.1 _2013 in four design scenarios similar to our case studies: prototype building for elementary school in Chicago and Los Angeles, and mid-size office building in Atlanta and Miami. The specification of the prototype buildings with their minimum requirements is listed in table 6.5. We are going to investigate the flexibility of design and the guidance of the design method as well as the probability of having more efficient product by comparing our proposed method with the ASHRAE prescriptive method in these prototype cases.

Table 6.5 ASHRAE 90.1-2013 prototype spec and minimum requirements

Variables			Unit	Chicago elementary school	Los Angeles elementary school	Atlanta medium size office	Miami medium size office
Form	1	Gross floor area	m2	6871	6871	4982	4982
	2	Number of floors	_	1	1	3	3
	3	Floor height	m	4	4	4	4
	4	Aspect ratio	_	1	1	1.5	1.5
Envelope	5	S-Window to wall ra	_	0.4	0.35	0.33	0.33
	6	E-Window to wall ra	_	0.4	0.35	0.33	0.33
	7	N-Window to wall ratio		0.4	0.35	0.33	0.33
	8	W-Window to wall ratio		0.4	0.35	0.33	0.33
	9	Envelope heat gain c	J/m2K	370,000	370,000	370,000	370,000
	10	Air leakage	m3/h per	3.1	3.1	1.7	1.7
	11	Opaque UValue	W/m2K	0.511	0.698	0.698	3.293
	12	Opaque absorption c	_	0.83	0.7	0.7	0.83
	13	Opaque emissivity	_	0.92	0.85	0.85	0.92
	14	Roof UValue	W/m2K	0.21	0.232	0.232	0.272
	15	Roof absorption co.	_	0.83	0.7	0.7	0.83
	16	Roof emissivity	_	0.95	0.85	0.85	0.95
	17	Window UValue	W/m2K	2.839	3.406	3.406	3.69
	18	Window emissivity	_	0.92	0.92	0.92	0.92
	19	Window SHGC	_	0.4	0.25	0.25	0.25
	20	South Overhang	degree	0	0	0	0
	21	South Fin	degree	0	0	0	0
	22	EastOverhang	degree	0	0	0	0
	23	East Fin	degree	0	0	0	0
	24	North Overhang	degree	0	0	0	0
	25	North Fin	degree	0	0	0	0
	26	West Overhang	degree	0	0	0	0
	27	West Fin	degree	0	0	0	0
Internal	28	Cooling Setpoint	Celsius	24	24	24	24
	29	Cooling setback	Celsius	27	27	27	27
	30	Heatiing setpoint	Celsius	21	21	21	21
	31	Heating setback	Celsius	16	16	16	16
	32	Occupancy	m2/perso	5	5	20	20
	33	Appliance total	W/m2	10	15	8	8
	34	Lighting	W/m2	15	15	10	10
	35	DHW	liter/m2/	5	5	5	5

6.2.1. Exploring Design Flexibility

We should first answer the question of how we can measure the extent to which design freedom has been maintained. In the context of building design, we define design freedom as the extent to which a design can be “adjusted" while still meeting its design requirements (Simpson, Rosen et al. 1998). Most literature in engineering design associated design freedom or design flexibility with the number of options one might have in order to meet the requirements. Clevenger et al. (Clevenger and Haymaker 2011), for instance, define alternative space flexibility, ASF, as the average number of option changes between any two alternatives divided by the number of variables. Since we are dealing with the notion of probability distributions for each design parameter instead of discrete design options, and we are comparing two methods, we will evaluate the ranges a designer would have in a similar design context using prescriptive and the inverse performance-based approaches, and compare them against each other.

The design-associated requirements in ASHRAE 90.1 are limited to windows to wall ratio in facades as well as thermal properties of roof, wall and glazing. These requirements are listed in tables 6.5 for the four aforementioned prototype buildings. The energy performances of these buildings are calculated in EPC and presented in table 6.6, which corresponds to the maximum thermal energy demand of those prototypes. These buildings are also modeled using the inverse approach; the geometry, occupancy, thermal setpoints and other scenarios have been assigned similar to the prototype. By assuming that we would like to have our energy performance objective to be equal or less than the ASHRAE prototypes maximum energy performance, we are going to estimate the values of windows to wall ratio and material properties, and compare them with the prescriptive ones, as depicted in figure 6.8.

Table 6.6 Thermal energy performances of the four ASHRAE prototype buildings

Prescriptive: ASHRAE90.-2013 prototype	Chicago elementary school	Los Angeles elementary school	Atlanta medium size office	Miami medium size office
Thermal demand	130.61	83.79	65.48	133.62

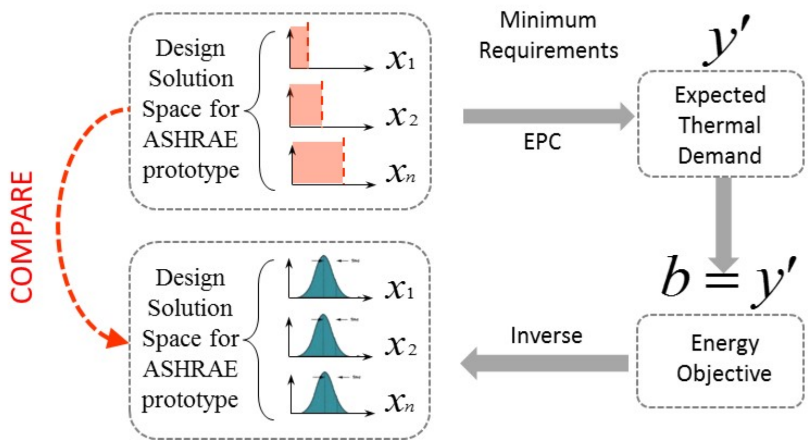


Figure 6.8 Validating hypothesis II by comparing design spaces

Tables 6.7 to 6.10 list the ranges of acceptable values for the eight design parameters, both from ASHRAE prescriptive method and inverse performance-based method. Figures 6.9 to 6.12 also demonstrate the distributions of these values. The differences between the design option ranges for each parameter, divided by the prescriptive method range is called "increased design flexibility", and considered as a metric to evaluate if we have a wider range of options for design parameters in the inverse approach compared to ASHRAE 90.1 2013 codes.

$$Increased\ Design\ Flexibility = \frac{Range\ of\ Design\ Option\ Scape\ in\ Inverse\ Method}{Range\ of\ Design\ Option\ Space\ in\ Prescriptive\ Method}$$

Increased design flexibility of 1 means that both method provide the same level of flexibility for designers. Any number more than 1 represents the higher level of flexibility or freedom the inverse method can provide the designers with. The last columns in the following tables (table 6.7 to 6.10) shows increased design flexibility corresponds to each considered design variables. As seen in a large number of cases, designers will have more flexibility or freedom to choose from the whole design option space using inverse approach.

Table 6.7 Acceptable ranges parameters in prescriptive vs. inverse approach, Chicago school

Chicago Elementary School	Prescriptive (ASHRAE 2013 Prototype)		Performance-Based (ASHRAE 2013 Prototype)		Increased Design Flexibility
	Min	**Max**	**Min**	**Max**	
South WWR	0	40%	0	96%	2.40
East WWR	0	40%	0	100%	2.49
North WWR	0	40%	0	94%	2.36
West WWR	0	40%	0	100%	2.49
Wall Uvalue	0.2	0.51	0.2	1.23	3.32
Roof Uvalue	0.1	0.21	0.1	1.15	9.54
Window SHGC	0.04	0.40	0.04	0.85	2.25
Window Uvalue	0.7	2.84	0.70	2.35	0.77

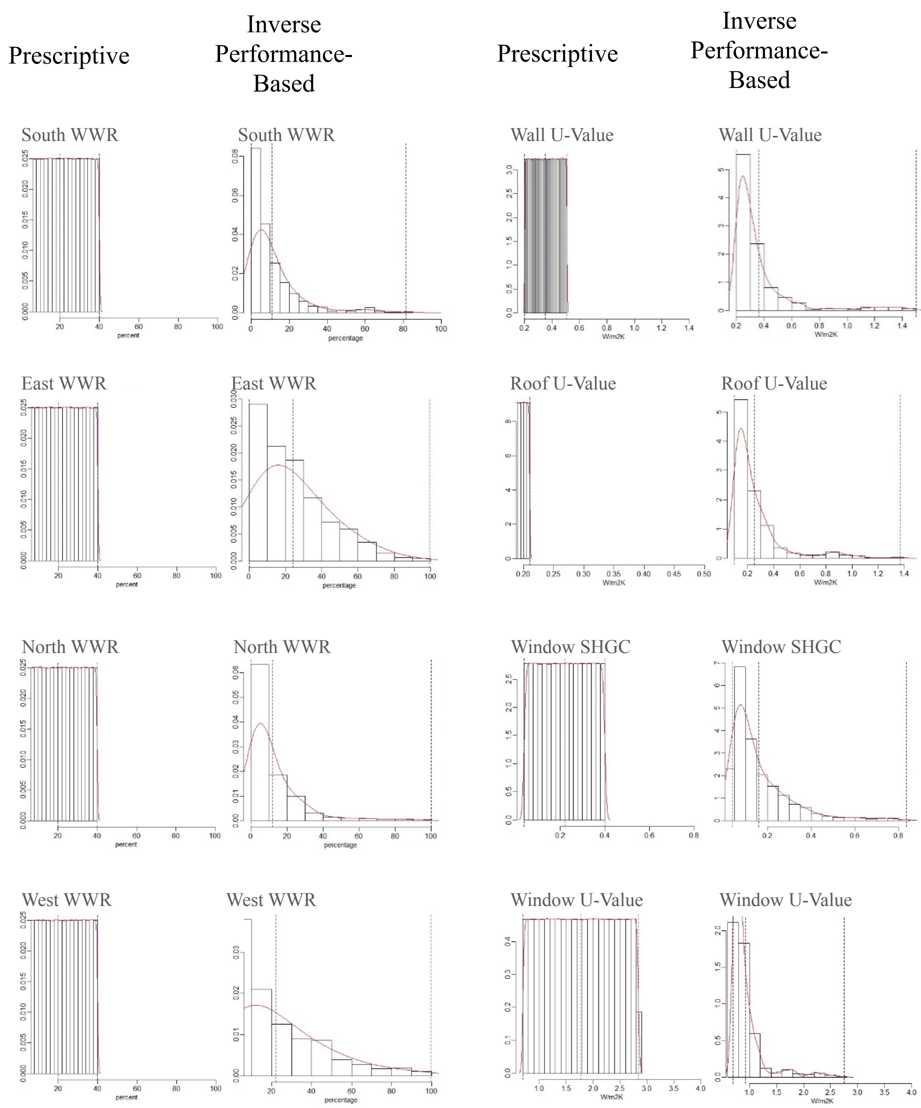


Figure 6.9 Acceptable parameters distributions in prescriptive vs. inverse approach, Chicago school

Table 6.8 Acceptable ranges parameters in prescriptive vs. inverse approach, LA school

Los Angeles Primary School	Prescriptive (ASHRAE 2013 Prototype)		Performance-Based (ASHRAE 2013 Prototype)		Increased Design Freedom
	Min	Max	Min	Max	
South WWR	0	40%	0	96%	2.41
East WWR	0	40%	0	100%	2.50
North WWR	0	40%	0	97%	2.42
West WWR	0	40%	0	100%	2.50
Wall Uvalue	0.2	0.69	0.2	1.50	2.65
Roof Uvalue	0.1	0.23	0.1	1.50	10.77
Window SHGC	0.04	0.25	0.04	0.65	2.90
Window Uvalue	0.7	3.40	0.70	4.00	1.22

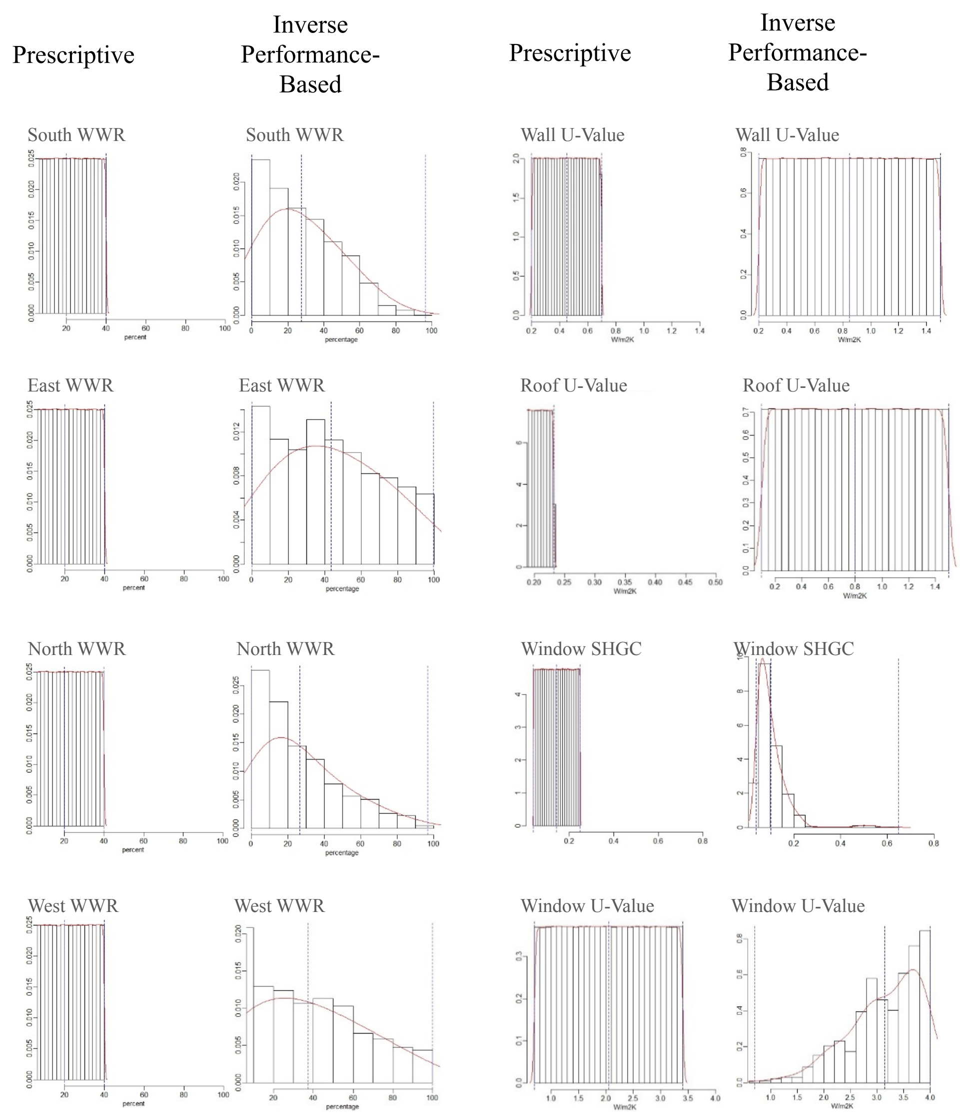


Figure 6.10 Acceptable parameters distributions in prescriptive vs. inverse approach, LA school

Table 6.9 Acceptable ranges parameters in prescriptive vs. inverse approach, Atlanta office

Atlanta Med-Office	Prescriptive (ASHRAE 2013 Prototype)		Performance-Based (ASHRAE 2013 Prototype)		Increased Design Freedom
	Min	Max	Min	Max	
South WWR	0	40%	0	76%	1.89
East WWR	0	40%	0	95%	2.38
North WWR	0	40%	0	95%	2.38
West WWR	0	40%	0	100%	2.49
Wall Uvalue	0.2	0.69	0.2	1.48	2.61
Roof Uvalue	0.1	0.23	0.1	1.49	10.70
Window SHGC	0.04	0.25	0.04	0.53	2.35
Window Uvalue	0.7	3.40	0.7	3.99	1.22

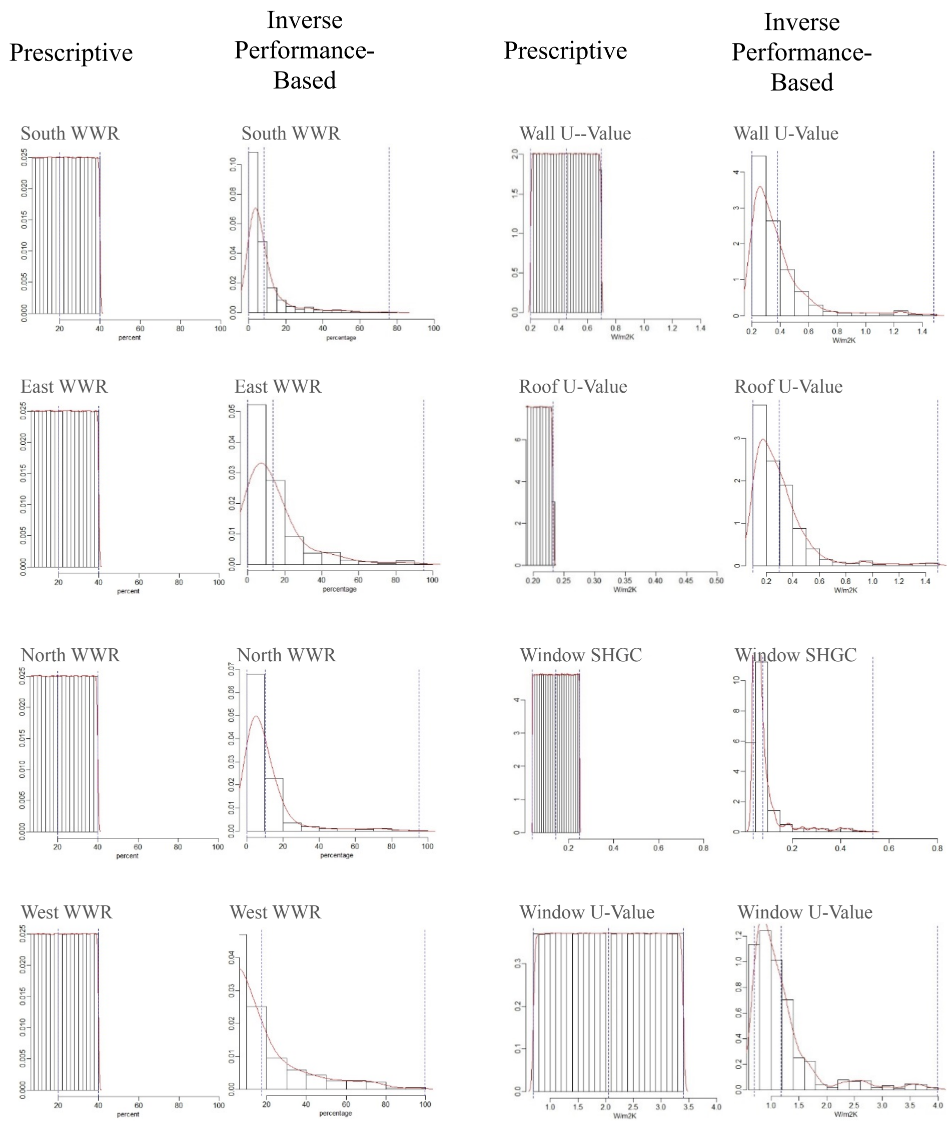


Figure 6.11 Acceptable parameters distributions in prescriptive vs. inverse approach, Atlanta office

Table 6.10 Acceptable ranges parameters in prescriptive vs. inverse approach, Miami office

Miami Med-Office	**Prescriptive** (ASHRAE 2013 Prototype)		**Performance-Based** (ASHRAE 2013 Prototype)		**Increased Design Freedom**
	Min	**Max**	**Min**	**Max**	
South WWR	0	40%	0	52%	1.31
East WWR	0	40%	0	95%	2.38
North WWR	0	40%	0	55%	1.37
West WWR	0	40%	0	99%	2.48
Wall Uvalue	0.2	3.29	0.2	1.48	0.41
Roof Uvalue	0.1	0.27	0.1	1.50	8.22
Window SHGC	0.04	0.25	0.04	0.53	2.33
Window Uvalue	0.7	3.69	0.7	4.00	1.10

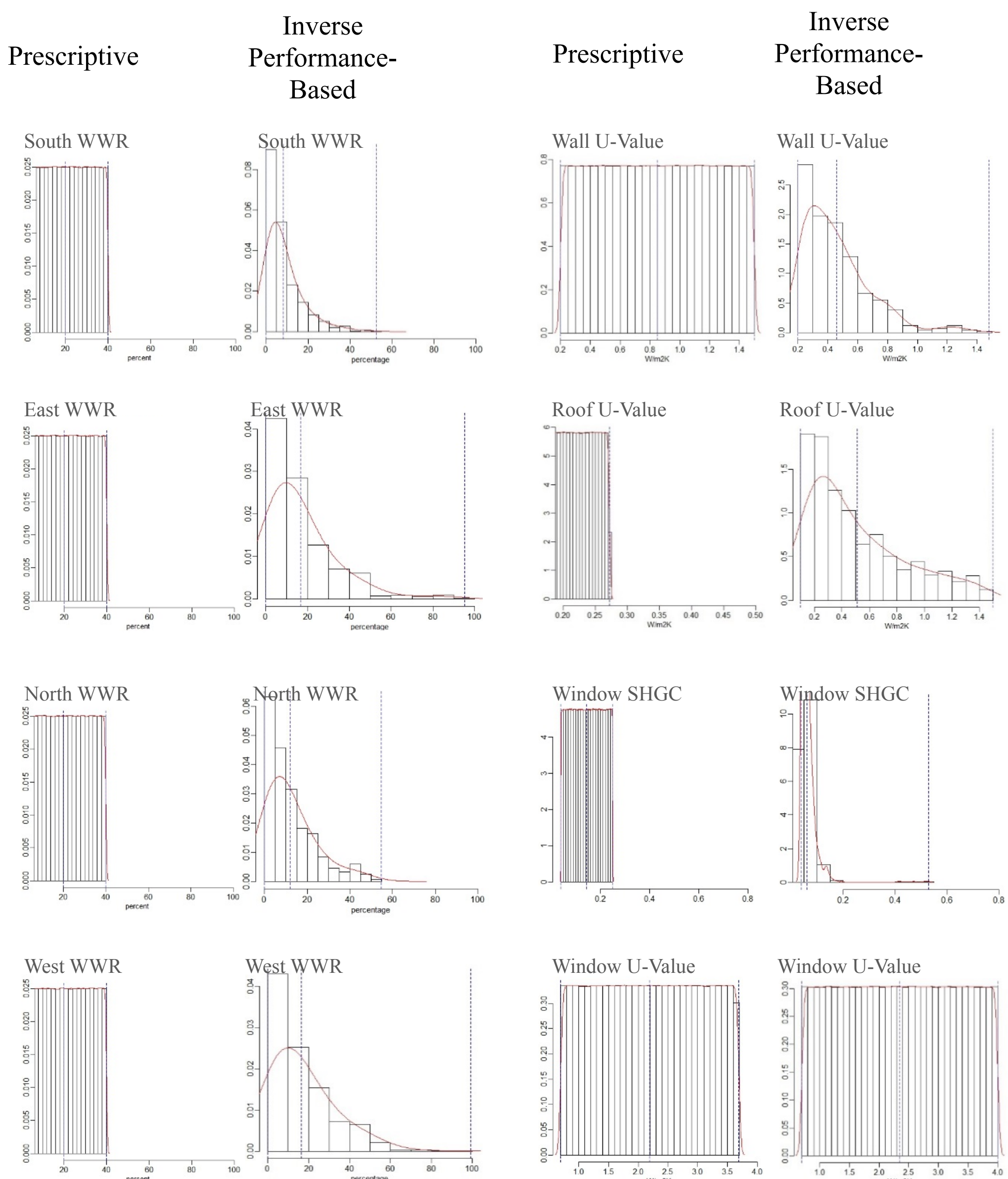


Figure 6.12 Acceptable parameters distributions in prescriptive vs. inverse approach, Miami office

6.2.2. Exploring Design Information and Guidance

There are several metrics for measuring the design knowledge and guidance a method can provide designers with. Suh (Suh 1990), whose work is perhaps the most well-known, has developed two global principles that serve as guidelines during design. According to him, a good design is one that maintains the independence of functional requirements with minimum information content. The concept of minimizing the information content has been introduced in the field of information theory by Shannon (Shannon 2001) and is associated with information entropy. Information entropy shows how much information there is in a message. This notion of information by Shannon is different from what we are using in every-day's language, and depicts the level of ambiguity of a message (Khan and Angeles 2011). Therefore we want to minimize information to minimize ambiguity and maximize guidance.

If $I(x)$ is the information content of x,

$$I(x) = \log_b 1/P(x) = -\log_b P(x)$$

Shannon defined the entropy H of a random variable x with the discrete and continuous probability density functions $P(x)$ as:

$$H(x) = E[I(x)]$$

$$H(x) = \sum P(x)I(x) = -\sum P(x)\log_b P(x) : \ for\ discrete\ variables$$

$$H(x) = \int P(x)I(x)dx = -\int P(x)\log_b P(x)\,dx \ : \quad for\ continuous\ variables$$

where E is the expected value operator and b is the base of the logarithm used. Common value of b is 2. Based on this formula, Shannon entropy is calculated as the expected value of the information contained in a message: the probability distribution associated with an event multiplies by the level of the information of the event make a distribution whose expected value is entropy. In general, more uncertain event corresponds to more information it contains and less guidance it provides. Uniform distribution over a design space represents maximum entropy, and single certain design represents zero entropy.

In order to evaluate how much the proposed inverse approach can guide designers, we are measuring and comparing entropy level in design option space derived from each of two methods of inverse method and prescriptive methods. The same design scenarios of the previous section are evaluated and compared using entropy metric, and the results are shown in tables 6.11 to 6.14.

Table 6.11 Entropy of the design parameters associated with prescriptive and inverse approaches, Chicago elementary school

Chicago Elementary School	**Entropy of Prescriptive Method**	**Entropy of Inverse Method**
South WWR	2.00	0.26
East WWR	2.00	0.26
North WWR	2.00	0.20
West WWR	2.00	0.32
Wall Uvalue	1.25	0.31
Roof Uvalue	0.35	0.23
Window SHGC	2.15	0.54
Window Uvalue	2.69	0.20

Table 6.12 Entropy of the design parameters associated with prescriptive and inverse approaches, Los Angeles elementary school

Los Angeles Primary School	**Entropy of Prescriptive Method**	**Entropy of Inverse Method**
South WWR	2.00	0.30
East WWR	2.00	0.31
North WWR	2.00	0.32
West WWR	2.00	0.32
Wall Uvalue	1.91	3.32
Roof Uvalue	1.12	3.32
Window SHGC	1.37	0.09
Window Uvalue	3.03	0.69

Table 6.13 Entropy of the design parameters associated with prescriptive and inverse approaches, Atlanta mid-size office building

Atlanta Med-Office	Entropy of Prescriptive Method	Entropy of Inverse Method
South WWR	2.00	0.16
East WWR	2.00	0.25
North WWR	2.00	0.23
West WWR	2.00	0.29
Wall Uvalue	1.91	0.42
Roof Uvalue	1.12	0.35
Window SHGC	1.37	0.09
Window Uvalue	3.03	0.94

Table 6.14 Entropy of the design parameters associated with prescriptive and inverse approaches, Miami mid-size office building

Miami Med-Office	Entropy of Prescriptive Method	Entropy of Inverse Method
South WWR	2.00	0.29
East WWR	2.00	0.32
North WWR	2.00	0.29
West WWR	2.00	0.31
Wall Uvalue	3.32	0.43
Roof Uvalue	1.52	0.44
Window SHGC	1.37	0.10
Window Uvalue	3.17	3.32

As seen in the table, entropy level of inverse approach has lower value compared to prescriptive method, representing less ambiguity and more guidance this method can provide. These results and the concept of entropy can also be understood better by looking at the figures 6.9 to 6.12 of previous section: the uniform distributions associated with the prescriptive method implies the indifferences and lower level of guidance associated with the codes for those variables; as long as designers follow the minimum requirements of the guidelines, they are accepted to have an energy efficient design. However, the non-uniform distributions of the design variables resulted from the inverse modeling implies that going with the parameters values with higher probability increase the chances of the objective fulfillment.

6.3. VALIDATION OF HYPOTHESIS III

Comparing the energy performance resulting from the prescriptive and performance-based approaches is challenging. As mentioned before, there is no explicit performance objective in prescriptive method; the goal is to reduce the energy consumption, and the codes are implemented to increase the possibility of reducing building energy use. In the performance-based approach, however, we consider explicit energy performance objectives. In the proposed inverse approach, in particular, the energy performance objective is subjective; the estimated values for design parameters depend on how strictly the design team defines their objective, and subsequently the energy performance resulting from those design parameter estimates would vary based on the predefined objective. As a result, it is impossible to have a general comparison between the results of these two approaches.

In more restricted scenarios, however, we will be able to compare the results of these two approaches. Consider the ASHRAE prototype buildings we assessed in the previous section; we assume that the design team plans to design a building with similar floor area and specification as prototype, but with different design form including different massing, orientation, aspect ratio, and shading device configurations. Any building design will comply with ASHRAE prescriptive method as long as it follows the minimum requirements for windows to wall ratio and material thermal properties. We run the analysis to see how different design for the same scenario as ASHRAE prototype will perform while it follows the requirements. Figures 6.13 represent the frequencies of thermal energy performance in four prototype buildings, by following the codes while using various design forms.

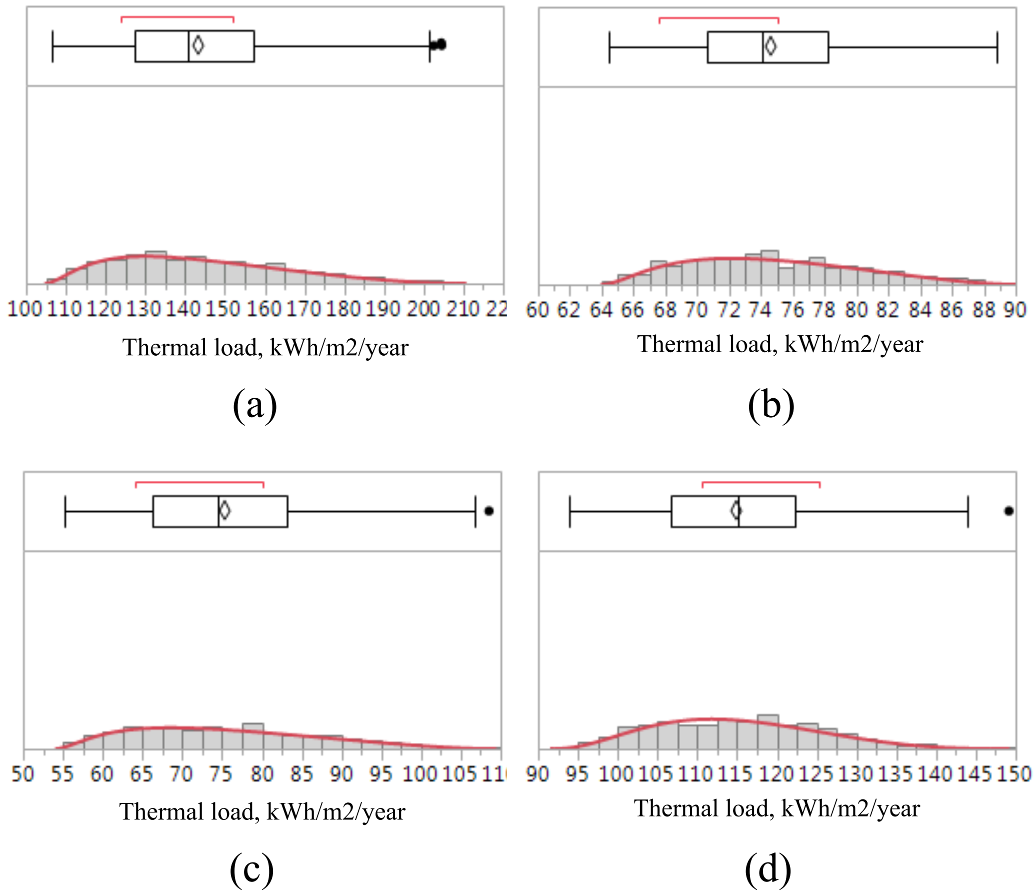


Figure 6.12 The frequency distributions of thermal energy demand, by following the AHRAE codes while having various design form; (a) School building in Chicago; (b) School building in Los Angeles, (c) medium-size office building in Atlanta, and (d) medium-size office building in Miami

On the other hand, in the inverse approach, the other design parameters such as the massing and orientation will be estimated probabilistically, and their distribution depends on the strictness of the energy performance objective as well as the other decided parameters' value. By assuming that the design team will use the same material properties and windows to wall ratio as prescriptive method, and the objective is to have equal or less energy performance as the mean value of the distributions in figure 6.13, we would like to investigate how the estimated design parameters will perform regarding energy performance. Figure 6.14 shows graphically what we compare for the third hypothesis.

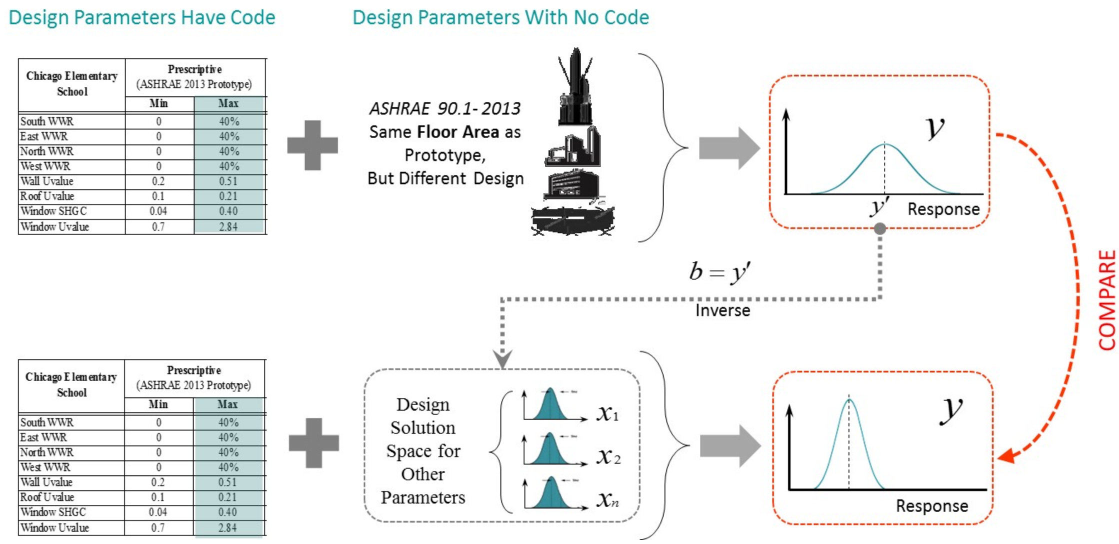


Figure 6.14 Validation process of hypothesis III

Figures 6.15 to 6.18 are the design solution spaces for the non-code design parameters resulted from using inverse approach. The results of the energy performance associated with prescriptive versus inverse methods are shown in figures 6.19 to 6.22 and tables 6.11 to 6.14.

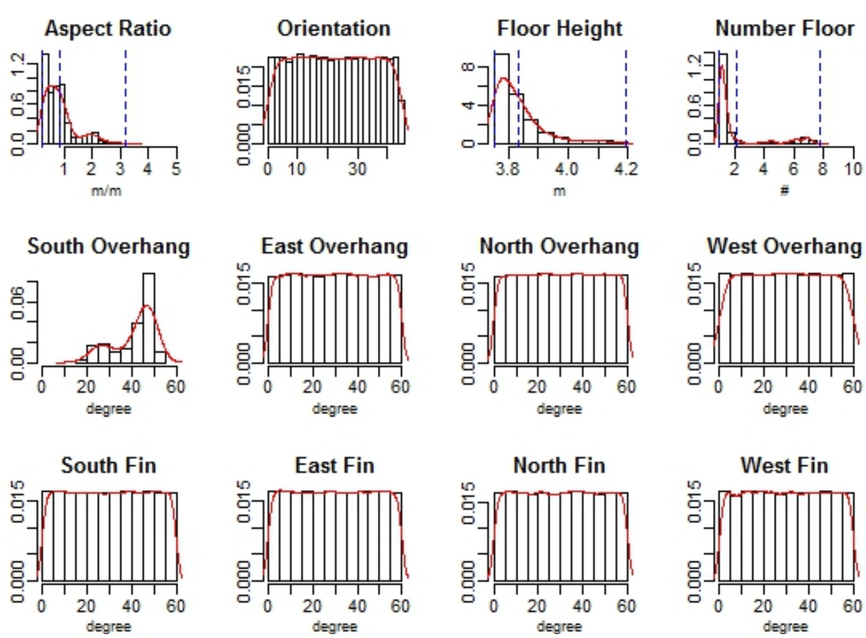


Figure 6.15 Design solution spaces for non-code parameters, Chicago elementary school

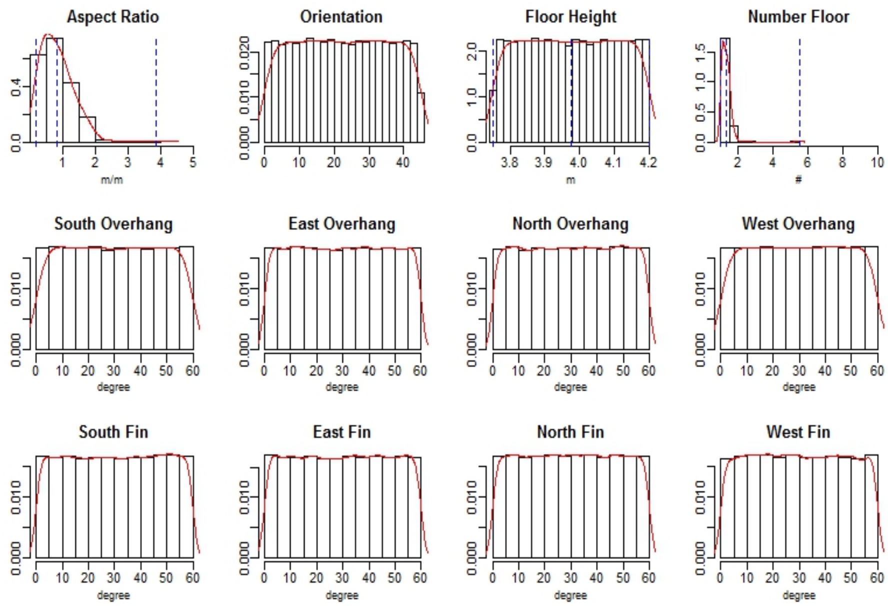


Figure 6.16 Design solution spaces for non-code parameters, LA elementary school

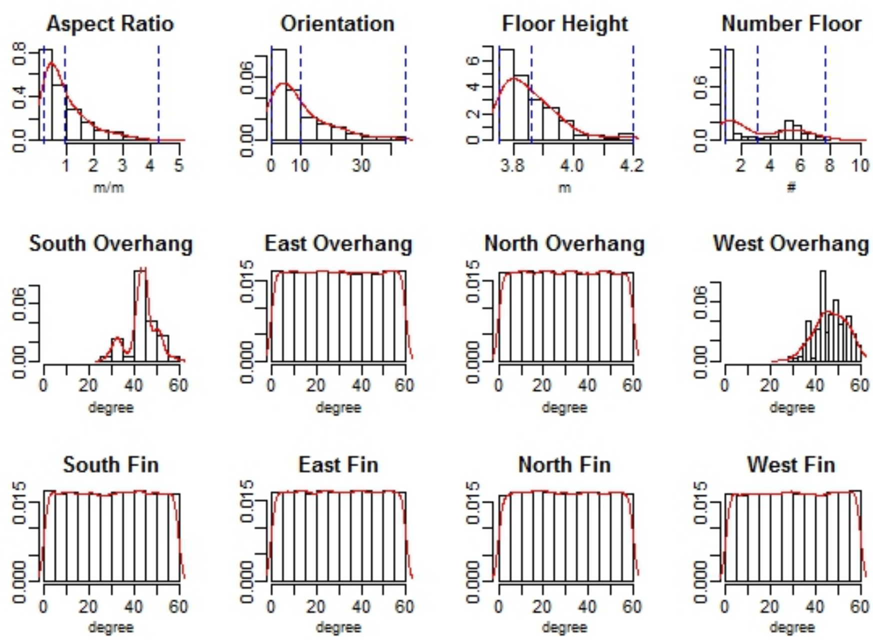


Figure 6.17 Design solution spaces for non-code parameters, Atlanta office

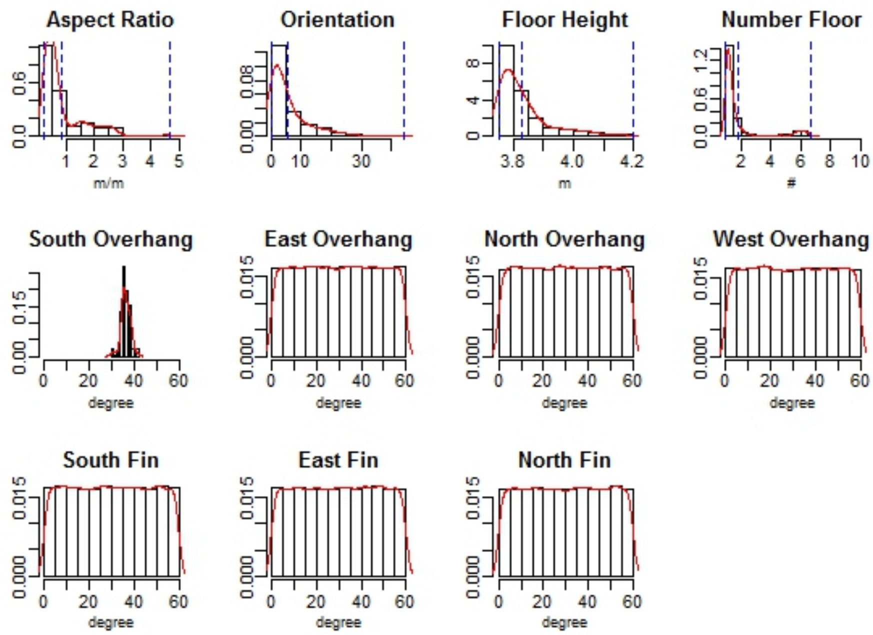


Figure 6.18 Design solution spaces for non-code parameters, Atlanta office

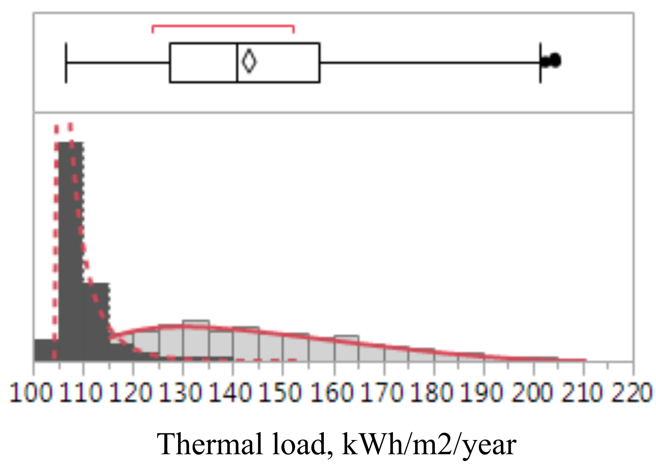


Figure 6.19 Energy performance distribution, prescriptive method (shown in grey color) versus inverse method (black color), Chicago school

Table 6.15 Energy performance distribution, prescriptive vs. inverse approach, Chicago school

Chicago Elementary School	**Probabilistoc Results**			
	Min Performance	**Max Performance**	**Mean Performance**	**Std Dev**
Prescriptive: ASHRAE90.-2013 prototype minimum requirement designs	106.43	204.56	143.16	20.52
ASHRAE90.-2013 mean performance as implicit objective for inverse approach	**143.16**			
Performance-based: Inverse approach	104.43	136.44	109.12	4.72

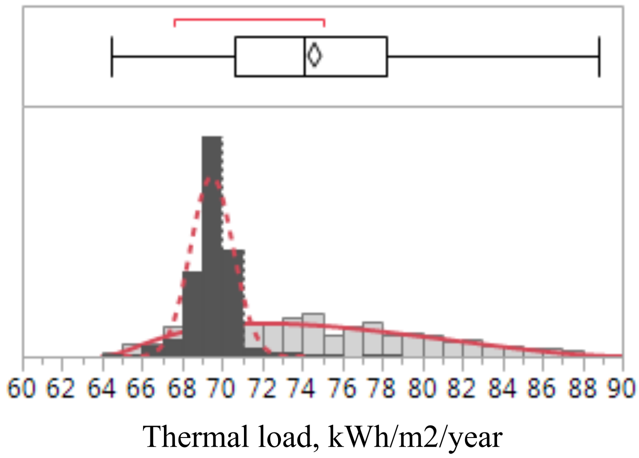


Figure 6.20 Energy performance distribution, prescriptive method (shown in grey color) versus inverse method (black color), Los Angeles school

Table 6.16 Energy performance distribution, prescriptive vs. inverse approach, Los Angeles school

Los Angeles Primary School	**Probabilistoc Results**			
	Min Performance	**Max Performance**	**Mean Performance**	**Std Dev**
Prescriptive: ASHRAE90.-2013 prototype minimum requirement designs	64.48	88.86	74.64	5.23
ASHRAE90.-2013 mean performance as implicit objective for inverse approach	**74.64**			
Performance-based: Inverse approach	64.85	78.09	69.49	1.06

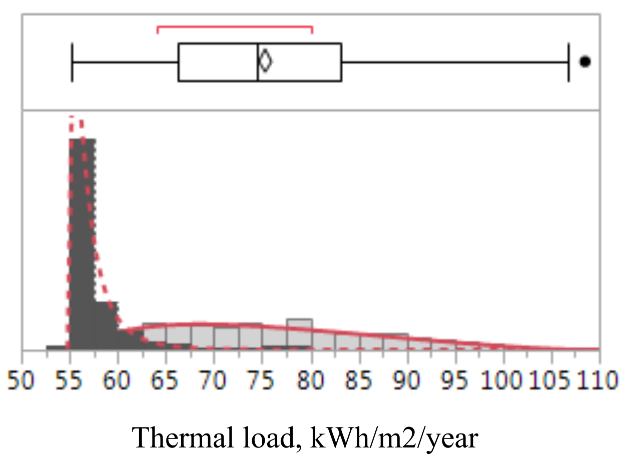


Figure 6.21 Energy performance distribution, prescriptive method (shown in grey color) versus inverse method (black color), Atlanta office

Table 6.17 Energy performance distribution, prescriptive vs. inverse approach, Atlanta office

Atlanta Med-Office	Probabilistoc Results			
	Min Performance	Max Performance	Mean Performance	Std Dev
Prescriptive: ASHRAE90.-2013 prototype minimum requirement designs	55.14	108.54	75.28	11.08
ASHRAE90.-2013 mean performance as implicit objective for inverse approach	**75.28**			
Performance-based: Inverse approach	54.84	78.68	57.53	3.44

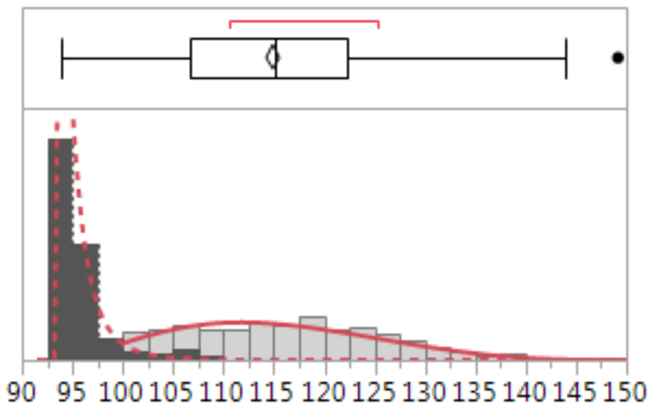


Figure 6.22 Energy performance distribution, prescriptive method (shown in grey color) versus inverse method (black color), Miami office

Figure 6.18 Energy performance distribution, prescriptive vs. inverse approach, Miami office

Miami Med-Office	Probabilistoc Results			
	Min Performance	Max Performance	Mean Performance	Std Dev
Prescriptive: ASHRAE90.-2013 prototype minimum requirement designs	94.00	149.16	114.94	9.85
ASHRAE90.-2013 mean performance as implicit objective for inverse approach	**114.94**			
Performance-based: Inverse approach	93.24	109.64	95.54	2.62

As depicted in these figures, the probability of having lower energy consumption is much higher in inverse approach compared to prescriptive approach; the minimum energy use is similar, and the maximum value of inverse approach is less than the expected value of prescriptive method. As mentioned before, the definition of the energy performance objective in these examples are subjective; by defining different goals and doing analysis at different stages of design when more or less parameters have been decided upon, we would get different results compared to the prescriptive method. Once again it shows the challenge of these types of comparison. The goal of having such examples in validation is to represent the capability of the proposed modeling approach in providing more design flexibility, guidance, and higher probability of fulfilling energy efficiency objectives.

6.3. SUMMARY

This chapter was dedicated to validations of the three hypotheses derived from the application of the inverse modeling at the early stage of design. Each hypothesis is validated using a particular procedure. In hypothesis one, we have proven that the solutions of the proposed inverse modeling are valid candidates to meet desired energy objective with the defined level of confidence. In addition to validating the accuracy of the proposed method, we have also proven this method to help designers in the design process, by increasing the exploration capability and guidance while providing freedom in design compared to prescriptive methods. Using the probabilistic approach, this method has been compared to similar design scenarios in examples of ASHRAE prototype, and has proven to have higher probability of fulfilling the desired energy performance.

CHAPTER 7

CLOSURE

7.1. SUMMARY AND CONCLUSION

At present, the building industry lacks a consistent and systematic approach to decision-making at the early stage of design; during the divergent phase of design decision making, when concepts are generated, there is no practical framework within which designers generate more promising alternatives regarding energy performance; and during the convergent phase, when concepts are evaluated and selected, there is no algorithm within which designers can validate their decisions and provide confidence in their decisions. The influence of designers' confidence in decisions is essential in the exploration of the design space and the evolution of a design through decision-making, which is not considered in current approaches. The current energy analysis models are inherently deterministic, and their typical use is likewise deterministic. This implies that the independent variables are known with certainty, which is not the case in general. Another important characteristic of design is its iterative and sequential process of decision-making, which is not reflected in current practice.

In order to overcome these deficiencies, this study proposed a new systematic method based on linear inverse modeling (LIM) that could generate plausible ranges for design parameters given a preferred thermal energy performance at the early stage of architectural design. In contrast to the conventional "forward modeling" in building performance analysis in which the design parameters are considered input and the energy performance are output, the "inverse modeling" deals with the performance objective as input and the design parameters are inferred as the output of the analysis.

Toward developing the inverse approach in energy-conscious building design, it is first proven that the thermal energy demand in a particular building operation-and-climate condition, calculated in normative EPC, can be expressed as a linear regression model. Such a claim was tested through exploration of four scenarios of building operation and climate zones, and four linear regression models representing thermal demand as a function of the most significant parameters were developed. The linear regression models along with the constraints on the values of building design variables as well as the objective energy performance were used in linear inverse models to estimate solution spaces for design parameters corresponding to the objective energy performance. It should be noted that the objective energy performance was defined probabilistically, as the desire of designers to have their design energy performance to be equal or less than a specific value, with a preferred level of confidence.

Outputs of inverse modeling for design parameters, as seen in four case studies, represented the estimation of each design parameter probabilistically given the desired energy performance. The cases we explored showed that by using the proposed method, rather than calculating a single "best" solution for design parameters, we could produce a large number of "likely" solutions, that both fitted the data and any other requirements that were used. The ranges of the different likely results fitted well with the goal of the design to give a designer the freedom to choose among feasible options that had a high likelihood of meeting objectives. Therefore, applying the proposed method helped designers in:

- Providing a clear step-wise approach that supported design exploration through combining the divergent (generation) and convergent (evaluation) phases of design process
- Highlighting significant parameters regarding energy performance for a variety of design scenarios

- Incorporating the undecided parameter uncertainty as the fundamental concept and driver in decision-making at the early stage of design, when the level of unknowns, undecided, and subsequently uncertainties are high, and subsequently providing confidence in decision-making
- Embodying the iterative nature of the architectural design in the approach by updating information as new decisions are made, and continually changing to accommodate new understanding of specifications, requirements, or preferences of other designers or stakeholders
- Emphasizing the multiple solutions that can account for the design problem by providing distributions, showing the likelihood of properties of parameters fulfilling preferred objective
- Enabling designers to define the energy performance objective subjectively based on the requirements of the project, and therefore find the solution space accordingly
- Increasing design knowledge by determining how the design variables affect the system performance and how the design variables change as a result of different energy performance objectives
- Enabling trade-off study and posing and answering several "what-if" questions during the design process.
- Maintaining design freedom and providing potentially larger design space compared to prescriptive methods.

To better understand the results of the proposed inverse modeling approach in building design, one should notice that at the very early stage of the analysis, when none or a few of the parameters have been decided, the resulting solution space often does not provide tangible guidance. The results of the analysis looked more similar to feasibility analysis and represented the ranges of the parameters in the solution space, or the parameters values that had a probability of zero, which showed there was not any possibility of having those values in the solution space.

The thesis then validated the hypotheses by verifying the accuracy of the results of the inverse method as well as proving its capabilities by comparing it with ASHRAE 90.1 2013 guidelines. It was proven that the solutions of the proposed inverse problem were valid candidates to meet stakeholder preference and objective; in comparison to the current prescriptive approach, the proposed performance-based method helped designers with the design process by providing more design guidance and freedom; and in comparison to the current prescriptive approach, the proposed performance-based method gave designers more confidence and leaded them to a higher probability of achieving the performance objective. In addition to aforementioned advantages, there are two points worth noting regarding the analysis time and computational effort. If such inverse models along with the library of all regression models are developed, the time to run each iterate of analysis is in average 15 seconds, and it does not require special expertise in the field of energy analysis or optimization and statistics in order to run the analysis and interpret results. This thesis research contributes to the body of knowledge pertaining to building energy modeling and decision making at the early design stage, and its framework can be used by researchers in academia, by architects in industry, as well as by policy makers in city.

7.2. FUTURE WORK

- *Feasibility of using linear regression models for thermal demand out of EPC for other design scenarios:* this study verified the feasibility of using linear regression model for two building types in four climate zones. In all four cases, the regression fitted models could explain at least 84.7 percent of the total variance from normative model, EPC, which sufficiently reflected the overall distribution as well as individual sample values of the normal building energy model. More case studies are necessary to confirm the feasibility of the substituting linear regression model for normative models across various building types and locations. If confirmed to be feasible for all scenarios, developing a library of reduced-order regression models is the next step.

- *Feasibility of using inverse approach for other building performances or other design stages:* this study verified the feasibility of using inverse approach for design exploration and decision making regarding energy performance at the early stage of design. This approach can be explored and tested for application in more advanced stages of design, or for other building performances such as delivered energy, CO2 emission, cost, and lighting performance.
- *Implementation in current CAD tools:* in order to increase the applicability of the proposed method, particularly for industry, the future work can be the integration of the proposed computations into current CAD tools. Creating a Revit plug-in, by developing mapping between the CAD Autodesk Revit design environment (Vandezande, Krygiel, & Read, 2014) and a statistical computational infrastructure (R), is suggested. The library including all of the regression models have to be used in the statistical model's database. In such a plugin, the users initiate with defining the type and location of the building, and will be exposed to the significant design parameters affecting thermal load (sum of cooling and heating load). At the same time, the designer can explore all possible thermal performance for that building type-and-location, and defines his/her preference on the energy performance. After identifying the decided versus undecided parameters and assign constraints, the solution space showing the probability distribution of the design parameters will be shown. This analysis process can be done iteratively after deciding about each parameter to see how the updated decisions will affect the distribution on the rest of the parameters. Hence the user

would have full control over the parameters and the preferred performance and their status.

- *Using Bayesian Inference to estimate design parameters range at the early stage of performance-based design:* this study proposed and explored the application of linear inverse modeling for energy related design exploration. One of the other methods that could be used with similar concept and foundation is Bayesian inference. By considering the same regression models as representation of the energy performance in a particular design scenario as well as the same method of energy objective definition, one can assign the constraints on design variable as the prior and calculate the posteriors of those design variable given the energy objective.

APPENDIX A

REGRESSION MODELS FOR FOUR DESIGN SCENARIOS

This appendix illustrates the regression models used developed and used in the inverse modeling for four design scenarios. y is sum of the heating and cooling loads, and x_i are design variables listed on table 4.1 page 62.

$$\begin{aligned} 100\log(y_{Chicago}) &= 228.119 + \frac{1150.84}{\log(x_1)} + 2.57x_2 + 10.234x_3 + 1.462x_4 + 9.619x_6 \\ &+ 6.061x_7 + 11.541x_8 + 3.119x_9 + 10.648x_{11} + 8.125x_{12} \\ &+ 10.717x_{15} + 6.119x_{18} + 10.767x_{20} + 0.025x_{21} - 5.90x_{29} \\ &- 1.161x_{30} + 6.041x_{31} + 1.976x_{32} + 154.24/x_{33} + 0.147x_{34} \end{aligned}$$

$$\begin{aligned} 100\log(y_{LosAngeles}) &= 408.874 + \frac{937.003}{\log(x_1)} + 2.04x_2 + 0.978x_4 + 14.979x_6 + 5.684x_7 \\ &+ 15.251x_8 + 12.17x_9 - 2.757x_{11} - 4.841x_{18} + 79.191x_{20} \\ &- 13.689x_{29} - 2.233x_{30} + 4.786x_{31} + 2.019x_{32} + \frac{110.844}{x_{33}} \\ &+ 1.835x_{34} + 1.876x_{35} \end{aligned}$$

$$\begin{aligned} 100\log(y_{Atlanta}) &= 247.953 + \frac{1247.49}{\log(x_1)} + 2.269\,x_2 + 7.27x_3 + 1.623x_4 - 5.274x_5 \\ &+ 15.924x_6 + 8.145x_7 + 13.414x_8 + 5.783x_9 + 5.517x_{11} \\ &+ 4.936x_{12} + 7.029x_{13} + 6.001x_{15} + 2.292x_{18} + 41.879x_{20} \\ &- 0.091x_{21} - 0.051x_{28} - 8.985x_{29} - 1.843x_{30} + 5.947x_{31} \\ &+ 2.645x_{32} + \frac{176.706}{x_{33}} + 1.279x_{34} + 1.146x_{35} \end{aligned}$$

$$\begin{aligned} 100\,log(y_{Miami}) &= 375.91 + \frac{11526.43}{log(x_1)} + 1.821x_2 + 8.388x_3 + 1.47x_4 - 16.913x_5 \\ &+ 18.165x_6 + 8.931x_7 + 14.554x_8 + 7.8469x_9 + 2.115x_{11} + 4.42x_{12} \\ &+ 3.224x_{15} + 163.105x_{20} - 0.0848x_{21} - 0.048x_{25} - 6.50x_{29} \\ &- 2.445x_{30} + 1.823x_{31} + 10.981x_{32} + 181.92/x_{33} + 1.645x_{34} \\ &+ 1.703x_{35} \end{aligned}$$

APPENDIX B

ASHRAE 90.1 2013 GUIDELINES FOR FOUR DESIGN SCENARIOS

This appendix shows the ASHRAE 90.1 2013 codes and standards associated with building design and envelope for the three climate zones corresponding to four case studies: 1A, 3A, 3B, 5A. Climate zone of 3A and 3B have the same building envelope codes.

Table B.1 Building envelope requirements for climate zone 1 (A, B, C)

Opaque Elements	Nonresidential		Residential		Semiheated	
	Assembly Maximum	Insulation Min. R-Value	Assembly Maximum	Insulation Min. R-Value	Assembly Maximum	Insulation Min. R-Value
Roofs						
Insulation Entirely above Deck	U-0.048	R-20 c.i.	U-0.039	R-25 c.i.	U-0.218	R-3.8 c.i.
Metal Building[a]	U-0.041	R-10 + R-19 FC	U-0.041	R-10 + R-19 FC	U-0.115	R-10
Attic and Other	U-0.027	R-38	U-0.027	R-38	U-0.081	R-13
Walls, above Grade						
Mass	U-0.580	NR	U-0.151[b]	R-5.7 c.i.[b]	U-0.580	NR
Metal Building	U-0.094	R-0 + R-9.8 c.i.	U-0.094	R-0 + R-9.8 c.i.	U-0.352	NR
Steel Framed	U-0.124	R-13	U-0.124	R-13	U-0.352	NR
Wood Framed and Other	U-0.089	R-13	U-0.089	R-13	U-0.292	NR
Wall, below Grade						
Below Grade Wall	C-1.140	NR	C-1.140	NR	C-1.140	NR
Floors						
Mass	U-0.322	NR	U-0.322	NR	U-0.322	NR
Steel Joist	U-0.350	NR	U-0.350	NR	U-0.350	NR
Wood Framed and Other	U-0.282	NR	U-0.282	NR	U-0.282	NR
Slab-on-Grade Floors						
Unheated	F-0.730	NR	F-0.730	NR	F-0.730	NR
Heated	F-1.020	R-7.5 for 12 in.	F-1.020	R-7.5 for 12 in.	F-1.020	R-7.5 for 12 in.
Opaque Doors						
Swinging	U-0.700		U-0.500		U-0.700	
Nonswinging	U-1.450		U-0.500		U-1.450	

Fenestration	Assembly Max. U	Assembly Max. SHGC	Assembly Min. VT/SHGC	Assembly Max. U	Assembly Max. SHGC	Assembly Min. VT/SHGC	Assembly Max. U	Assembly Max. SHGC	Assembly Min. VT/SHGC
Vertical Fenestration, 0%–40% of Wall		(for all frame types)			(for all frame types)			(for all frame types)	
Nonmetal framing, all	U-0.50[c]			U-0.50[c]			U-0.93		
Metal framing, fixed	U-0.57[c]			U-0.57[c]			U-1.20		
Metal framing, operable	U-0.65[c]	SHGC-0.25	1.10	U-0.65[c]	SHGC-0.25	1.10	U-1.20	NR	NR
Metal framing, entrance door	U-1.10[c]			U-1.10[c]			U-1.10[c]		
Skylight, 0%–3% of Roof									
All types	U-0.75	SHGC-0.35	NR	U-0.75	SHGC-0.35	NR	U-1.80	NR	NR

* The following definitions apply: c.i. = continuous insulation (see Section 3.2), FC = filled cavity (see Section A2.3.2.5), Ls = liner system (see Section A2.3.2.4), NR = no (insulation) requirement.

a. When using the R-value compliance method for metal building roofs, a thermal spacer block is required (see Section A2.3.2).

b. Exception to Section 5.5.3.2 applies for mass walls above grade.

c. For locations in Climate Zone 1 with a cooling design temperature of 95°F and greater, see Section 5.5.4.3 for the maximum U-factors for vertical fenestration.

Table B.2 Building envelope requirements for climate zone 3 (A, B, C)

Opaque Elements	Nonresidential		Residential		Semiheated	
	Assembly Maximum	Insulation Min. R-Value	Assembly Maximum	Insulation Min. R-Value	Assembly Maximum	Insulation Min. R-Value
Roofs						
Insulation Entirely above Deck	U-0.039	R-25 c.i.	U-0.039	R-25 c.i.	U-0.119	R-7.6 c.i.
Metal Building[a]	U-0.041	R-10 + R-19 FC	U-0.041	R-10 + R-19 FC	U-0.096	R-16
Attic and Other	U-0.027	R-38	U-0.027	R-38	U-0.053	R-19
Walls, above Grade						
Mass	U-0.123	R-7.6 c.i.	U-0.104	R-9.5 c.i.	U-0.580	NR
Metal Building	U-0.094	R-0 + R-9.8 c.i.	U-0.072	R-0 + R-13 c.i.	U-0.162	R-13
Steel Framed	U-0.077	R-13 + R-5 c.i.	U-0.064	R-13 + R-7.5 c.i.	U-0.124	R-13
Wood Framed and Other	U-0.089	R-13	U-0.064	R-13 + R-3.8 c.i. or R-20	U-0.089	R-13
Wall, below Grade						
Below Grade Wall	C-1.140	NR	C-1.140	NR	C-1.140	NR
Floors						
Mass	U-0.074	R-10 c.i.	U-0.074	R-10 c.i.	U-0.137	R-4.2 c.i.
Steel Joist	U-0.038	R-30	U-0.038	R-30	U-0.052	R-19
Wood Framed and Other	U-0.033	R-30	U-0.033	R-30	U-0.051	R-19
Slab-on-Grade Floors						
Unheated	F-0.730	NR	F-0.540	R-10 for 24 in.	F-0.730	NR
Heated	F-0.860	R-15 for 24 in.	F-0.860	R-15 for 24 in.	F-1.020	R-7.5 for 12 in.
Opaque Doors						
Swinging	U-0.700		U-0.500		U-0.700	
Nonswinging	U-0.500		U-0.500		U-1.450	

Fenestration	Assembly Max. U	Assembly Max. SHGC	Assembly Min. VT/SHGC	Assembly Max. U	Assembly Max. SHGC	Assembly Min. VT/SHGC	Assembly Max. U	Assembly Max. SHGC	Assembly Min. VT/SHGC
Vertical Fenestration, 0%–40% of Wall		(for all frame types)			(for all frame types)			(for all frame types)	
Nonmetal framing, all	U-0.35			U-0.35			U-0.87		
Metal framing, fixed	U-0.50	SHGC-0.25	1.10	U-0.50	SHGC-0.25	1.10	U-1.20	NR	NR
Metal framing, operable	U-0.60			U-0.60			U-1.20		
Metal framing, entrance door	U-0.77			U-0.68			U-0.77		
Skylight, 0%–3% of Roof									
All types	U-0.55	SHGC-0.35	NR	U-0.55	SHGC-0.35	NR	U-1.70	NR	NR

* The following definitions apply: c.i. = continuous insulation (see Section 3.2), FC = filled cavity (see Section A2.3.2.5), Ls = liner system (see Section A2.3.2.4), NR = no (insulation) requirement.

a. When using the R-value compliance method for metal building roofs, a thermal spacer block is required (see Section A2.3.2).

Table B.3 Building envelope requirements for climate zone 5 (A, B, C)

Opaque Elements	Nonresidential Assembly Maximum	Nonresidential Insulation Min. R-Value	Residential Assembly Maximum	Residential Insulation Min. R-Value	Semiheated Assembly Maximum	Semiheated Insulation Min. R-Value
Roofs						
Insulation Entirely above Deck	U-0.032	R-30 c.i.	U-0.032	R-30 c.i.	U-0.063	R-15 c.i.
Metal Building[a]	U-0.037	R-19 + R-11 Ls or R-25 + R-8 Ls	U-0.037	R-19 + R-11 Ls or R-25 + R-8 Ls	U-0.082	R-19
Attic and Other	U-0.021	R-49	U-0.021	R-49	U-0.034	R-30
Walls, above Grade						
Mass	U-0.090	R-11.4 c.i.	U-0.080	R-13.3 c.i.	U-0.151[b]	R-5.7 c.i.[b]
Metal Building	U-0.050	R-0 + R-19 c.i.	U-0.050	R-0 + R-19 c.i.	U-0.094	R-0 + R-9.8 c.i.
Steel Framed	U-0.055	R-13 + R-10 c.i.	U-0.055	R-13 + R-10 c.i.	U-0.084	R-13+R-3.8 c.i.
Wood Framed and Other	U-0.051	R-13 + R-7.5 c.i. or R-19 + R-5 c.i.	U-0.051	R-13 + R-7.5 c.i. or R-19 + R-5 c.i.	U-0.089	R-13
Wall, below Grade						
Below Grade Wall	C-0.119	R-7.5 c.i.	C-0.092	R-10 c.i.	C-1.140	NR
Floors						
Mass	U-0.057	R-14.6 c.i.	U-0.051	R-16.7 c.i.	U-0.107	R-6.3 c.i.
Steel Joist	U-0.038	R-30	U-0.038	R-30	U-0.052	R-19
Wood Framed and Other	U-0.033	R-30	U-0.033	R-30	U-0.051	R-19
Slab-on-Grade Floors						
Unheated	F-0.520	R-15 for 24 in	F-0.510	R-20 for 24 in.	F-0.730	NR
Heated	F-0.688	R-20 for 48 in.	F-0.688	R-20 for 48 in.	F-0.900	R-10 for 24 in.
Opaque Doors						
Swinging	U-0.500		U-0.500		U-0.700	
Nonswinging	U-0.500		U-0.500		U-1.450	

Fenestration	Nonresidential Assembly Max. U	Nonresidential Assembly Max. SHGC	Nonresidential Assembly Min. VT/SHGC	Residential Assembly Max. U	Residential Assembly Max. SHGC	Residential Assembly Min. VT/SHGC	Semiheated Assembly Max. U	Semiheated Assembly Max. SHGC	Semiheated Assembly Min. VT/SHGC
Vertical Fenestration, 0%–40% of Wall		(for all frame types)			(for all frame types)			(for all frame types)	
Nonmetal framing, all	U-0.32	SHGC-0.40	1.10	U-0.32	SHGC-0.40	1.10	U-0.45	NR	NR
Metal framing, fixed	U-0.42			U-0.42			U-0.62		
Metal framing, operable	U-0.50			U-0.50			U-0.70		
Metal framing, entrance door	U-0.77			U-0.68			U-0.77		
Skylight, 0%–3% of Roof									
All types	U-0.50	SHGC-0.40	NR	U-0.50	SHGC-0.40	NR	U-0.98	NR	NR

* The following definitions apply: c.i. = continuous insulation (see Section 3.2), FC = filled cavity (see Section A2.3.2.5), Ls = liner system (see Section A2.3.2.4), NR = no (insulation) requirement.

a. When using the R-value compliance method for metal building roofs, a thermal spacer block is required (see Section A2.3.2).

b. Exception to Section 5.5.3.2 applies for mass walls above grade.

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> A general framework for the development of future Intelligent Integrated Building Design Systems IIBDS is discussed. After introducing a general integration framework, both from a process as well as from a product view, it is argued that a key-requisite for devlelopment-strategies towards full-blown design systems is an open, conceptual approach, avoiding premature excessive implementation efforts and adhering closely to (emerging) standards, such as STEP. Results from the European R&D project COMBINE (Computer Models for the Building Industry in Europe), jointly carried out by 15 partners from 8 countries are presented. COMBINE deals primarily with data integration in the early design stage, the ‘design actors’ being both from the architectural (plan-layout in sketch design phase) as well as consultancy (energy performance and HVAC) disciplines.

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> The conceptual design phase of any project is, by its very nature, a vibrant, creative and dynamic period. It can also be disorganised with much backtracking accompanying the exchange of information between design team members. The transfer of information, ideas and opinion is critical to the development of concepts and as such, rather than being recognised as merely a component of conceptual design activity, it needs to be understood and, ultimately, managed. This paper describes an experimental workshop involving fifteen design professionals in which conceptual design activity was tracked, and subsequently mapped, in order to test and validate a tentative design framework (phase and activity model). The nature of the design progression of the various teams is captured and analysed, allowing a number of conclusions to be drawn regarding both the iterative nature of this phase of design and how teams of professionals actually design together.

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This article motivates the need for more research into the interaction between building design and building analysis in a process context. To provide a context for this discussion, the text focusses on a specific problem: the selection of energy saving building components. A strategy to provide (computational) support for their selection is presented; this strategy is then used to discuss the design support provided by current building analysis tools and to assess probable outcomes of current developments. Finally, a new research project revisiting fundamental issues of design analysis integration is presented.

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This paper describes MIDAS (a memory for initial design of aircraft subsystems), a system that applies insights and techniques from case-based reasoning (CBR) to aid engineers in the design of utility subsystems early in the development of a new aircraft concept. Our goal is to demonstrate the usefulness and practicality of a particular approach to building a corporate design memory. MIDAS is an instance of a general class of systems we call Case-Based Design Aids (CBDAs). A CBDA provides a designer with convenient access to multimedia presentations that highlight the outstanding good and bad points of previous designs. MIDAS was developed as a joint project of the Georgia Tech AI Lab and Lockheed Aeronautical Systems Company's Advanced Design Division. It is the first CBDA to be built largely by domain experts; the AI team primarily provided an (evolving) tool kit, and advice.

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> The task of quickly producing preliminary and detailed structural schemes which are safe and economic requires an experienced engineer. It has always been the case that speed is of the essence in such a competitive market as the construction industry and any tools that the engineer can utilise can only be to his benefit. The engineer will use his past experience and knowledge of structural behaviour and design to produce structural schemes. Some of the early scheme information will use the engineers past experience and in some cases simple rules of thumb or simple calculations. Most of the early calculations will involve simple, easy to use analytical techniques, including rule of thumb methods. Often though the structure is too complex to use such methods, or perhaps the engineer does not know of a simple yet accurate preliminary design method for this particular structure. The detailed analysis and design presently utilises software which is often operated by junior engineers or technicians. The output from this work requires checking in some way to ensure the analysis/design is correct. Sometimes it is possible to use simple calculations to obtain an approximate view of the structures overall behaviour and thus check the design. Also it is possible to use simple rules of thumb to do the same job, but collecting large numbers of these simple calculations or rules is difficult. Many engineers have developed these themselves or have collected these quick design aids over many years of working in different offices on a variety of structures and using different materials.

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